Swine Flu and The Effect of Compulsory Class Attendance on Academic Performance

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ABSTRACT

We use a natural experiment that relaxed class attendance requirements for one school year to explore students' marginal propensity to skip class, and to examine the effects of their absences on scholastic outcomes. We exploit exogenous variation resulting from a one-time policy Greece implemented allowing high school students to miss 30 percent more class hours without penalty during the 2009-10 academic year, a period when officials feared outbreaks of swine flu. Using a new dataset, we analyze which students missed more classes, and the effect of these absences on scholastic outcomes across the distribution of student ability, income, and peer quality. We find that while the swine flu itself did not affect the student population, the relaxed class attendance policy caused an increase in absences of roughly 10 hours per student, with more absences taken by those who had higher academic performance records, have academically weaker peers in their classes, or who live in poorer neighborhoods. End-of-year exam results show a positive effect of the relaxed attendance policy on grades across the ability distribution. The magnitude of the positive effect of absences on grades increases as we move to right of the ability distribution. Our results suggest that students who may have the resources or the human capital accumulation to learn outside the classroom may have lower performance when a strict attendance policy forces them to stay in class.

Keywords: human capital, returns to education, attendance, instrumental variables, natural experiment
JEL Classification: I26, J24

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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. Lecture learning is based on group learning, which may not be the optimal learning style for everyone. In a classroom, students compete for the attention and time of the instructor. Thus, their consumption of education induces externalities on one another. As a result, many students decide to skip class when given the opportunity. Therefore, if the optimal level of class attendance is below perfect, is compulsory class attendance beneficial for every student?

In this paper, we investigate the causal relationship between compulsory class attendance and exam performance. In our setting, high school students in Greece are allowed to be absent from school up to a certain number of school periods without penalty. Exceeding the upper limit is punished by grade retention. In 2009, the Hellenic Ministry of Education received information about an increasing number of Swine Flu cases around Europe. Though high-school students in Greece did not constitute a population at risk, the ministry nevertheless decided to take action. This action went into effect several months later, when the European swine flu pandemic was over. The unique, one-time-only reform increased the number of periods a student could miss without penalty. The ministry specified that students did not need to provide a doctor's note, or to seek their parents' approval to take up the extra absences. Our paper exploits variation from this natural experiment that increased the absence allowance of high school students by 34 school periods or 30 percent. The treatment offers exogenous variation by relaxing the time budget constraint of students, who maximize utility by allocating time between school and leisure. Using an Instrumental Variable approach, we identify the causal effect of class attendance on exam performance. We control for individual-specific heterogeneity by using longitudinal data on the exam performance of students in consecutive grades. The Swine Flu Reform allows us to mitigate endogeneity stemming from unobserved common shocks that vary across grades.

Students may miss class both when they are sick and when they are not sick. In the latter case, student may miss class to enjoy leisure or study. Absence due to sickness may decrease performance. Absence for reasons other than sickness may have a non negative effect on performance depending on how the time outside the classroom is spent. We exploit a natural experiment that allowed students to miss more classes without actually being sick. The effect of absences on performance estimated comes from absences that are not related to sickness.

We divide students into three groups. The first group includes students who never skip class, and attend no matter whether they have the option to skip or not. The second group of students skips class regularly. Those students choose to skip regardless of whether the class attendance policy is strict or loose. The third group of students chooses to attend class only when the class attendance policy is strict. Students who have the resources or enough human capital accumulation to sufficiently substitute class work with out-of-class individual work or tutoring belong in the third group. Our instrumental variables approach estimates the effect of absences on exam performance that is due to a relaxed class attendance policy. Returns to absences are identified for students who can replicate class activities outside the classroom that is, the group of students who are most likely to exploit the relaxed class attendance policy.

The relaxed attendance policy makes some students to skip class. Our findings show that for students whose class activities are not too costly to replicate outside the classroom, school absences increase exam performance. We can view this the other way around: A strict class attendance would reduce school absences for those students who would skip class if given lax attendance rules, could cause exam performance to decrease. A decrease in exam performance due to a strict attendance policy could stem from two sources. First, class learning could be sub-optimal for some students who have the resources to acquire human capital through other pedagogical methods. Intuitively, the larger the class, the less efficient class learning becomes because the instructor's time is divided among more learners. Second, class peer effects could affect individual exam performance. We do not know a priori whether students capable of learning outside the classroom receive positive or negative class peer effects when they must adhere to a strict attendance policy. Be that as it may, we know that students are assigned to classes using alphabetical order based on their last names. Lexicographical class assignment allows for heterogeneous environments where students from different points of the ability distribution interact with each other. Such environments may be conducive to disruptive behavior or acting up that leads the learning experience to deteriorate. Thus, while estimating returns to absences due to a relaxed class attendance policy we are measuring the net externality the rest of the class imposes on students capable of learning outside the classroom.

The contribution of our paper is threefold. First, we exploit variation stemming from a natural experiment to mitigate two sources of endogeneity: time-invariant, individual-specific, unobserved heterogeneity, such as parental supervision or personality traits; and grade-varying, common shocks such as teacher or student-age effect. Second, we use new, hand-collected transcript data from a random sample of 114 schools in Greece in order to provide evidence relevant across the ability distribution. Thus, we can answer the question: Who benefits from the school more, the good or the bad students? The natural experiment utilized in our paper didn't force students into taking action but merely relaxed one constraint of their utility- maximization problem. In other words, the element of choice remains in both the strict and the relaxed class attendance policy regimes. Thus the third novelty of our paper is that we are able to estimate the differential response to the relaxed constraint as well as differential returns to absences that may be induced by student or school characteristics. Moreover, the natural experiment increased the upper limit of unexcused absences. Unexcused absences can be absences in the middle of the day, and they do not require a doctor's note or a parent's approval. That means students choose which period and subject to skip. Therefore, the students may choose to skip English but attend mathematics in the same day. The estimates of returns to absence identified by this unique reform pertain to the situation where the students strategically choose which school periods to attend and to miss. Moreover, we delve into the reasons students choose to be absent from school. Because the exogenous policy change that we exploit for identification did not force students to skip class, and because not every student took advantage of the new policy to the same extent, we are able to explore the heterogeneous propensity to skip class across different observable student, school, and class characteristics.

The rest of the paper is organized as follows: Section 2 places in the literature, Section 3 provides a motivation in the context of economic theory, Section 4 provides a description of the institutional setting, Section 5 describes our data collection, Section 6 summarizes the data used, Section 7 describes the empirical strategy, and section 8 discusses our results. Section 9 contains robustness check for our results, and Section 10 concludes.

2 Our Place in The Literature

Educational interventions can be classified as taking one of two forms: those that improve the quality of the inputs of the production function and those that increase their quantity. Much of the work to date has focused on estimating the effects of interventions that targeted the quality of educational inputs, such as teacher quality, class size or classroom environment (Hanushek et al. 1999, Rivkin et al. 2005a, Hanushek 2003, Angrist and Lavy

1997, Krueger 2003) or measuring the effects of all school production factors on both the quantity and quality margins (Card and Krueger 1990, Loeb and Bound 1995, Betts 1995). Nevertheless, investment in resources are likely to happen concurrently. Historically, school districts with the longest term lengths were those with the highest paid teachers, making it difficult to disentangle the effects of interventions in quality from those in quantity. This work joins a strand of the literature focused on determining the returns to increasing the quantity of inputs, namely time in school, separately from changing their quality (Pischke 2007, Hansen 2011, Marcotte and Hansen 2010, Leuven et al. 2010, Sims 2008)

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 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 or negligible relationship between students' absenteeism and academic performance, or, in one case, a negligible relationship (Caviglia 2006). Evidence from the existing literature suggests that class attendance improves educational outcomes. 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 of the right tail of the ability distribution in a given population. Chen and Lin (2006) using a sample of 129 college students in Taiwan find a 4 percent 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 took 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 much as 18 percent. 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 (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, such as high schools. Fitzpatrick et al. (2011) use quasi randomness in the timing of kindergarten assessment to examine the effect of time spent in school on student achievement. Their estimates suggest that a year of schooling increases math and reading test scores by about one standard deviation above normal developmental gains. Aucejo and Romano (2016) exploit a North Carolina state policy that resulted in variation in the length of the school year to jointly es- timate the effect of high school attendance and the length of the school calendar on performance while controlling for student and teacher characteristics. They also use local flu prevalence data to instru- ment for absences. They find that 10 days of school absence reduce math scores by 5.5 percent and reading scores by 2.9 percent. In the context of Aucejo and Romano (2016), students skip class because of the flu, and, thus, they have no choice over which periods to skip.

3 Theoretical Motivation

Following Arulampalam et al. (2012) we build a theoretical model to motivate both our hypotheses and our empirical strategy. Suppose the representative student faces the following additively separable utility function:

$$U = u(s(c, h, a), l) \tag{1}$$

which is a function of leisure, l and the following educational production function

$$s = s(c, h, a) \tag{2}$$

where s is a measure of a student's educational performance, c is the amount of time the student spends in class, h is the amount of time the student spends in out-of-class learning activities, a captures individual characteristics such as ability, motivation, and effort. Suppose for simplicity that the marginal utility of s is one and the marginal utility of leisure is constant for every unit of time outside the classroom[2].

The objective of the student is to maximize utility from performance and leisure given their time constraint, which takes the following form:

$$c + h + l \leq T \tag{3}$$

where T is the maximum amount of available time in a given period. Assume initially that c and h in the production function are neither complements nor substitutes but independent. The student maximizes their utility by allocating their time efficiently between leisure, in class study, and out of class study. We assume there is no coordination among student in the decision of time allocation. Thus any peer effects are random and not the result of a collective behavior.

In reality, marginal products are likely to vary from person to person. A student faces the challenge of knowing whether in or out of class learning works best for them. In other words, students are supposed to know their relative marginal productivities of the inputs in their educational production function.

Assume that students have accurate information regarding the parameters in their own production function. This assumption may hold less for students in elementary school and more for high school students as the latter have had more learning experience. Assume also that the marginal products of study time in class and out of class are positive but exhibit diminishing returns and are independent of each other and of ability: $\frac{\partial s}{\partial c} := mpc > 0$, $\frac{\partial s}{\partial h} := mph > 0$, $\frac{\partial^2 s}{\partial c^2} < 0$, $\frac{\partial^2 s}{\partial h^2} < 0$, $\frac{\partial^2 s}{\partial c \partial h} = 0$, $\frac{\partial^2 s}{\partial c \partial a} = 0$, and $\frac{\partial^2 s}{\partial c \partial a} = 0$. We also assume $\frac{\partial s}{\partial a} > 0$. We will relax some of these assumptions later. Under these assumptions we can represent diagrammatically the solution to the problem of the utility-maximizing student.

In Figure 1a, we see that the utility-maximizing student will optimise at point A, choosing to attend c^* hours of class and engaging in $T - c^*$ hours of out of class study. Whether this involves absences from class will depend on the number of scheduled classes available to the student. In that sense, the school imposes a constraint on time. If there are significant external net benefits of attending class, then the number of classes supplied to the student, denoted by t_{cs}, is more likely to exceed the student's optimal number, thus

[2]The assumption of constant marginal utility of leisure is not crucial. Here is an example where we relax this assumption. Consider the following production function: $s = s(c, h, a)$. Suppose the utility function takes the following form: $U = u(s, l) = s(c, h, a) + \gamma\sqrt{l} = \alpha\sqrt{c} + \beta\sqrt{h} + \gamma\sqrt{l}$. Maximizing utility under the time constraint gives the following optimal time allocation: $\{c^*, h^*, l^*\} = \{\frac{\alpha^2}{\alpha^2+\beta^2+\gamma^2}, \frac{\beta^2}{\alpha^2+\beta^2+\gamma^2}, \frac{\gamma^2}{\alpha^2+\beta^2+\gamma^2}\}$

$t_{cs} > c^*$, as in Figure 1a. If now $t_{cs} < c^*$ as in Figure 1c, then the outcome will be inefficient as $mpc > mph$.

In the case described in Figure 1a, the optimising student will choose to miss $t_{cs} - c^*$ hours of class. At the margin, if students were required to attend t_{cs} hours of class, their academic performance would decrease as $mph > mpc$ for the marginal classes. Suppose that class attendance is compulsory but that absence is not penalized. Then the propensity of students to miss at least some fraction of the suboptimal $t_{cs} - c^*$ classes will depend on their attitudes to compliance, which we suppose it's randomly distributed across the student population, but may change with age. Then, under the assumptions of the model, class absences in the range $t_{cs} - c^*$ will be associated with higher performance. This may seem as a depart from the standard hypothesis in the literature that more absences decrease performance, but our prediction emerges from an optimizing setting in which choices are made under perfect information. At the margin, class attendance improves performance, but only up to an optimizing point.

Suppose now that we relax our assumption that factor inputs are independent and allow the marginal product of attending class to be positively correlated with ability, *ceteris paribus*: $\frac{\partial^2 s}{\partial c \partial a} > 0$. This case is represented in Figure 1c, where the mpc for more able students, mpc_2, lies above that of the less able, mpc_1. We see that utility-optimizing makes the more able students to skip fewer classes in comparison to less able ones: $c_2^* > c_1^*$ in Figure 1c. In a framework where class attendance is optional, performance will be greater for the more able students and, thus, will be negatively associated with class absence.

Moreover, mph can also be positively correlated with characteristics captured in a. For example, students from economically more advantaged backgrounds may have better to access to private tutoring, books, faster internet and other resources, which thereby result in a higher mph.In that case, whether c_2^* will be less or greater than c_1^* will depend on comparative advantage, that is the relative correlation of a with mpc and with mph.

In an econometric estimation of the effects of absence on performance, correlation between a and either c or h in the education production function given by equation 2 could potentially generate endogeneity bias if a is not perfectly observed. If more able students are less likely to be absent from class $c_2^* > c_1^*$, as in Figure 1c then the estimated adverse effect of absence on performance will be biased upwards, in absolute terms, through endogenous selection and the resulting ability bias. The empirical investigation of the effects of absence from class on performance should be constructed so as to allow for heterogeneous effects of this sort. This observation lies behind the design of our later estimation strategy. In the case in which $c_1^* > c_2^*$, then the direction of endogeneity bias will be downward but, again, the effects will be heterogeneous.

As we have seen, ability differences across students can affect absences from class through their influence on the educational production function, equation 2. But suppose now that there are differences across students in marginal utility of leisure, mul . In Figure 1d, we consider the effects of an exogenous increase in the marginal utility of leisure. In this case, there will be an increase in the number of classes missed along with an associated drop in performance. In the model, the marginal utility of leisure, mul , is taken as exogenous. In reality, mul is likely to be influenced by various arguments. For example, individual, family or even city characteristics may account for differences in marginal utility of leisure. The marginal utility of leisure may also be related to student ability, and hence to a in equation 2. If, for instance, more able students undertake more non-curricular activities, then mul will be positively correlated with ability. In this case, more able students will be more likely to miss class. Note also from Figure 1d that the effect of missing class will be greater for more able students as $mpc_2^* > mpc_1^*$. Again, unobserved differences in ability across students will create a bias in the estimated effect of absence on performance as part of the association between absence and performance is being explained by a differential propensity of the more able to be absent from class.

In summary, we have seen that, in an optimizing framework, the theoretical effect of absence on performance is ambiguous. If class attendance is compulsory and students differ only in a randomly-distributed propensity toward compliance, then absence will have a positive association with performance as the less compliant will be more likely to adhere to the optimal number of classes. If, on the other hand, students are heterogeneous in ability then they will be likely to choose different optimal levels of class attendance: if ability is associated with a comparative advantage in class attendance as in Figure 1c then the more able will have a higher attendance rate and absence will be associated with poorer educational performance. Ability might also be correlated with the marginal utility of leisure: if more able students have a higher opportunity cost of studying, then it is likely that they will attend fewer classes. In this case, class absence will be likely to have a positive association with performance. Estimation of the effects of absence on performance will be biased if ability is not observed or accurately proxied and the direction of bias will depend on the relative dominance of factors of the type we have identified. The model predicts that the magnitude of any effects of absence on performance will vary with student ability: if, for example, ability is relatively highly correlated with productivity of class attendance then the negative effect of absence on performance will be greatest for the more able students. Nevertheless, out-of-class productivity is also positively associated with more classed missed. Ability may also be correlated with out-of-class productivity in the sense that more able students are better at learning on their own. If out-of-class-productivity exceeds in-class productivity, i.e. if there is a comparative advantage in out-of-class learning, lower class attendance may be associated with higher performance. These considerations inform our choice of empirical estimation strategy.

The model we have outlined so far assumes that students have sufficient information to be able to select their optimal level of class attendance. In reality, this is unlikely and students will make mistakes, attending either more or fewer classes than would be privately efficient. If students systematically under-estimate the marginal product of class attendance, then absence will tend to have an adverse effect on performance. This tendency might also be correlated with ability, so that less able students miss more classes and suffer a further reduced level of performance.

Informed by this theoretical motivation on the optimizing behavior of individuals, our empirical strategy will involve: first, an analysis of the effects of a relaxed class attendance policy on absences, second, an attempt to identify causal effects of absence on student performance using the exogenous variation from the relaxed attendance policy, third, an investigation of whether and how any effects of the relaxed attendance policy on absences and school performance vary systematically with student, class, and school characteristics.

4 Institutional Setting

4.1 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; only around 8 percent of students attend private high school[3]. 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 characteristics, such as education and experience, are not taken into account for

[3]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.

the allocation of teachers to schools. By law, students' assignment to classrooms is based on alphabetical order.

Students in the Greek educational system are allowed to be absent from class for a limited number of hours in a given school year. Class absence can be either excused or unexcused. Total absences are the sum of excused and unexcused hours of class absence. Excused absences are whole day absences that the student provided for a doctor's note or a custodian -usually a parent came to school to sign off their child's absence. Class absence for less than a whole day cannot be excused and therefore count towards a student's unexcused absences. For example, if a student goes to school late in the morning or if she decides to skip school midday, these absences cannot be excused. Whole day absence from school that is not excused counts towards a student's unexcused absences. Under the current class attendance regulation, every student could have 50 hours of unexcused and 64 hours of excused absence from class within a given year. The penalty for exceeding the number of allowed absences is severe, requiring that a student repeat the grade.[4]

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 60 percent of school subjects are mandatory, and the remaining consist of electives and specialization courses. In Greece, unlike the situation typical of other educational systems, students remain in their assigned classrooms 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, subjects considered in our analysis.

All schools in Greece offer three academic tracks in the eleventh and twelfth grade. Each track offers different courses. The level of the track courses is comparable to the Advanced Placement (AP) courses found in the US educational system. There are three track courses in the eleventh grade, and four track courses in the twelfth grade. The Tracks are: Classics, Science and Information Technology(IT)[5]. All track courses are mandatory

[4]Near the end of the school year 2005-2006, a new bill was passed that included new, more lenient regulations regarding 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 the student's past Grade Point Average. In particular, every student who had received a Grade Point Average higher than 15/20 the previous school year (2004-05) was allowed more absences in the following school year (2005-06).

[5]Students attending the Classics track take Ancient Greek, Latin, and Philosophy in the 11th grade,

and available only for students within a track. Attending a particular track gives access to a set of college degrees relevant to the track attended. Exam scores in the track courses determine college admission. At the end of senior high school, students take national, standardized exams in the track courses in addition to Greek Language and one elective 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.

4.2 The 2009 Swine Flu Pandemic

In late spring 2009, the first, sporadic cases of swine flu surfaced in Europe. The 2009 flu pandemic in Europe was part of a pandemic involving a new strain of influenza, subtype H1N1. H1N1 is commonly called swine flu. The pandemic infected at least 125,550 people in Europe. There were 458 confirmed deaths in Turkey, 438 confirmed deaths in Russia, and 299 confirmed deaths in the United Kingdom.

Swine influenza was first proposed to be a disease related to human flu during the 1918 flu pandemic, when pigs became ill at the same time as humans. The first identification of an influenza virus as a cause of disease in pigs occurred later, in 1930. For the following 60 years, swine influenza strains were almost exclusively H1N1. Then, between 1997 and 2002, new strains of three different subtypes and five different genotypes emerged as causes of influenza among pigs in North America. The H1N1 form of swine flu is one of the descendants of the strain that caused the 1918 flu pandemic. As well as persisting in pigs, the descendants of the 1918 virus have also circulated in humans through the 20th century, contributing to the normal seasonal epidemics of influenza. However, direct transmission from pigs to humans is rare, with only 12 recorded cases in the United States since 2005.

According to the U.S. Centers for Disease Control and Prevention (CDC), in humans the symptoms of the 2009 swine flu H1N1 virus are similar to those of influenza and of influenza-like illnesses in general. Symptoms include fever; cough, sore throat, watery eyes, body aches, shortness of breath, headache, weight loss, chills, sneezing, runny nose, coughing, dizziness, abdominal pain, lack of appetite and fatigue. The 2009 outbreak

and Ancient Greek, Latin, Literature, and History in the 12th grade. Students attending the Information Technology track take Mathematics, Physics, and Programming in the 11th grade, and Mathematics, Physics, Computer Programming, and Business Administration in the 12th grade. Students attending the Science track take Mathematics, Physics, and Chemistry in the 11th grade, and Mathematics, Physics, Biology, and Chemistry in the 12th grade evidenced an increased percentage of patients reporting diarrhea and vomiting, as well. "The 2009 H1N1 virus was not zoonotic swine flu, as was not transmitted from pigs to humans, but from person to person through airborne droplets", we read in the Hellenic Hellenic Center for Disease Control and Prevention (HCDCP) annual report from 2010.

Influenza spreads between humans when infected people cough or sneeze, then other people are exposed by breathing in the virus or touching something with the virus on it. Vaccines are available for different kinds of swine flu. If a person becomes sick with swine flu, antiviral drugs can make the illness milder and make the patient feel better faster. The most common cause of death is respiratory failure. Other causes of death are pneumonia (leading to sepsis), high fever (leading to neurological problems), dehydration (from excessive vomiting and diarrhea), electrolyte imbalance and kidney failure. Fatalities are more likely in young children and the elderly.

The HCDCP reports describe the chronicle of the swine flu outbreak: On May 19, 2009, authorities confirmed the first case of swine flu in Greece. The infected person was a 19-year-old Greek student who studied in New York and who had flown to Greece a few days before becoming ill. He was hospitalized at Sismanogleion General Hospital of Athens, but was not considered to be gravely ill. The authorities contacted many of the passengers who sat near this patient on the plane, and examined them for suspicious symptoms. At that point in time Greece officials said they had enough anti-virals to cover 12 percent of the population. (European Union directives proposed that health officials have supplied on had to cover at least 10 percent of the population.). The 19-year-old was soon released, and none of the passengers in his flight were found to be infected. Looking back at newspaper articles from 2009 in conjunction with the HCDCP announcements we get an idea of how the swine flu spread in subsequent weeks after the first case: On June 14, 2009, the total number of cases in Greece had reached 20; on June 17, 25 total cases had been reported. On July 9, the total number of cases had reached 216, with 93 of these individuals having fully recovered; on July 14, the total number of cases had reached 323, with 200 having fully recovered. On September 16 the total number of cases had reached 2149.

Schools started on September 12, 2009. The number of new H1N1 cases started declining after October 2009 (Sypsa et al., 2011). The Hellenic Ministry of Education, indicating that it feared a recurrence of the outbreak, announced on April 12, 2010 a one-time-only increase in the number of hours of absence a student was allowed to make without penalty by 30 percent for the current academic year.

The upper limit of absences before and during the reform is given in Table 1. After the school year 2009-2010, the old attendance regulation was restored.

5 Data Collection

To study the effect of compulsory attendance on school performance we need information on class attendance and performance. Data on attendance are not centrally collected, and can only be found in the school archives. We have visited 134 schools and constructed a unique dataset on student transcripts from a large, randomized sample of high schools in Greece. For this study we focus on public schools (Full Sample: 110 schools, 51,666 students). We also use data from three experimental/charter schools (4,981 students) and five private schools (2,893 students) in our robustness checks. This novel dataset includes every student who attended one of the sampled schools between 2006 and 2012, and contains panel information from the following sources:

1. Administrative data from the high schools containing class identifier, class size [6], gender, year of birth, and year of graduation, information on the courses taken by a given student, and d exam results in each of the last three years of a given student's secondary education . For each student we also know how many hours were she was absent from class for each of the three years of high school (10th, 11th, and 12th grades). We know how many absence hours were excused by parents or with a doctor's note, and how many hours of students' absences remained unexcused. We do not have information on the schools students transfer from or to.

2. School-specific information, including the name of school, type of school (private, public[7], experimental[8])), and geographical location.

3. Average net income information for population within the postcode of the school (expressed in 2009 euros), provided by the Ministry of Finance.

4. Urban density information, provided by the Ministry of Internal Affairs. Urban areas are those with more than 20,000 inhabitants. We also match data on local population from the Hellenic Statistical Authority using the school postcode. Local population refers to city population or the population of the smallest unit of area obtained from the 2011 National Census.

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

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

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

5. Data on flu cases provided by the Hellenic Center of Disease Control and Prevention.

In our analysis we use administrative data provided by high schools in Greece. The map in Figure 2 shows the schools included in our data. We analyze course participation and grades at the student level for all three high school grades for the years between 2006 and 2012. High school students are assigned to classes by alphabetical order based on their last name. We know to which class each student is assigned, and we use this information to create peer-quality and peer-class-attendance measures. We also have some background characteristics, such as nationality, age and gender, which we use a check for the identification strategy, and to reduce the variance of the error term.

Measuring the causal effect of class attendance on grades requires data on attendance. For every class, attendance is registered by the instructor and two teacher-assistants. The assistants verify which students are present or absent, and gives the list of absentees to the instructor, who checks and signs it. All attendance lists are collected at the end of the day. The record is then digitized by a teacher who is responsible for notifying y parents about their child's attendance once per semester. Even if the administrative data contain no measurement error, the attendance rate is likely to have some inaccuracies for the following reason: The teacher responsible for keeping the attendance record may under-report the actual absences of a student who is extremely close to the cutoff. Going over the cutoff means that the student cannot be promoted to the next grade, and that the school must retain her. Nevertheless, this reason may not lead to an under- or over-estimation of the effect of absences on grades. To see this, note that the effect of absences on grades is estimated through an IV procedure, where a simple Wald-estimates equals: $\frac{E[G|D=1]-E[G|D=0]}{E[A|D=1]-E[A|D=0]}$, where G is the grade, A is number of absences in hours and D=1 if one is subject to the relaxed class attendance policy. First, underreporting the actual number of absences outside the year of treatment underestimates the hours of absence by students who were subject to the relaxed class attendance policy ($E[\widehat{A|D=0}] < E[A|D=0]$). Underreporting of absences outside the treatment years may happen because for some students the attendance policy is too strict for some students, and they find themselves too close to the grade retention cutoff. Second, underreporting the actual number of absences during the year of treatment underestimates the hours of absence by students who were subject to the relaxed class attendance policy ($E[\widehat{A|D=1}] < E[A|D=1]$). Underreporting of absences during the treatment years may happen because some students over-exploit the relaxed attendance policy, and when they find themselves too close to the grade retention cutoff; their teacher may underreport their absences to save them from the devastating charybdis of retention. We do not see any reason why the latter should be greater or smaller than the former. As long as underreporting remains stable over time, the estimated causal effect of absences on grades is unbiased.

6 Summary Statistics

Our initial panel consists of 57,380 individuals from 110 schools. Not all schools keep attendance records for every year. For 38,042 individuals from 102 schools we have full transcript information and attendance history. For 34,461 we have full transcript information and attendance history for at least two consecutive grades. For 21,514 individuals from 90 schools we have full transcript information and attendance history for three consecutive grades: 10th, 11th, and 12th grade. For 1,873 students there is missing age or gender information. Attrition can be either from transferring schools, dropping out, or grade retention. Grade retention can be either due to failure to obtain a grade point average of at least 9.5 out of 20, or due to missing more than 50 hours of class without a parent's approval or a doctor's note or 114 hours of class in total. Transcript information can be missing due to grade retention. When a student is grade retained we observe a note in the transcript that the student was retained along with the reason for his/her retention. If a student is retained because they went over the upper limit of absences they are not allowed to take the end-of-the-year exams and thus we observe missing values on the individual subject scores and the GPA for those students. Average grade retention is almost 4%. 1.3% of students is retained due to missing too many classes. We provide summary statistics for grade retention and grade retention due to absences in Tables 16 and 17 respectively. Grade retention due to absences is more common among lower performing students. Specifically 3.1% of students in the bottom quintile based on their midterm score in Mathematics end up being retained due to missing too many classes. Grade retention is more common among males than females: 5.1% in males and 2.7% in females. Grade retention has also higher incidence among students who are 18 or older: 19% compared to 3.3% for students younger than 18 years.

For our analysis, we use all students for whom we have full information in all three years (N = *19,641*). Table 3 summarizes the data used in our analysis split by treatment status. Treatment group consists of observation in the year 2010, while control group consists of observations in the years 2006, 2007, 2008, 2009, 2011, and 2012.

Our theoretical motivation described a situation where the optimal level of attendance may be lower than the required level of attendance. If this holds in the educational system that we examine in our study, we would expect the students to exploit in full their absences allowance, that is the number of hours of class they can miss without penalty. To investigate whether students' absences constraint is indeed binding we plot the distributions of absences under the two attendance policy regimes. Since -as we have mentioned- excused absences require either a doctor's note or a parent's approval, they are more costly compared to unexcused absences. For the absences constraint to be binding we would expect a disproportionate amount of student to miss as many hours of class as he/she can getting very close to the upper limit of absences. We would expect this to be more apparent for the less costly type of absence, unexcused absences, as the cost of providing a doctor's note or bringing a parent to school may not allow the students to fully exploit the excused absences limit.

In figure 3 we plot the density distribution of total absences under the old class attendance regulation. We see that a portion of the distribution piles up close to 114 hours, the upper limit of total absences. In figure 4 we plot the density distribution of total absences under the new class attendance regulation. We see that the right tail of the absences distribution occurs to the right of the old limit and to the left of new class absences limit. In figure 5 we plot the density distribution of unexcused absences under the old class attendance regulation. We see that the distribution of unexcused absences piles up close to 50 hours, the upper limit of unexcused absences. In figure 6 we plot the density distribution of unexcused absences under the new class attendance regulation. We see that around half of the density is to the right of the old limit and to the left of new class absences limit. Since the hours of absences under the old regulation pile up close to the limit, especially so when we look at the less costly type of class absence, unexcused absence, we see that students experienced a binding absences constraint under the old regulation. When the new attendance regulation increased the upper limit of absences a great part of the absences distribution shifted to the right of the old limit, suggesting that students exploited the lax attendance policy.

7 Identification Strategy

In this section we present our empirical strategy for identifying the causal effect of compulsory class attendance on student's attainment. Using our dataset we estimate returns to absences among high school students. The standard approach when estimating the effect of absences on school performance consists of regressing an individual's performance on the number of classes missed. Estimating returns to absences using OLS will lead to biased estimates of β. The main problem is that Absences may be correlated with omitted variables that also affect student performance. In other words, the correlation of Absences with the error term would bias the OLS estimates. A student's own personality, ability, and motivation, as well as his/her class, school, and family environment can affect his/her joint decision of attendance and effort.

To control for unobserved characteristics of the students as well as past input history, we employ the following lagged value-added specification:

$$\begin{aligned} Score_{i,s,c,g,t} =& \beta_0 + \beta_1 Absences_{i,s,c,g,t} + \beta_2 Score_{i,g-1} + \beta_3 X_{i,s,c,g,t} \\ &+ \beta_4 Class\ controls_c + Grade\ FE_g + School\ FE_s + \epsilon_{i,s,c,g,t} \end{aligned} \tag{4}$$

where $Score$ of student i, in grade g, school s, in classroom c, and in time t is a function of her hours of absence in grade g, school s and time t, some time-invariant factors that vary across grades, and grade varying student characteristics such as age. By including the lagged year performance in the regression model implies, according to the literature of teacher value added (Todd and Wolpin, 2003), that we no longer need to incorporate additional measures of ability or previous years inputs. $Score$ can be final exam score in mathematics, Greek, physics or the grade point average (GPA). Scores are standardized by school and grade. We also include controls for class characteristics such as peer quality, measured as the average lagged GPA of the class peers, and class engagement, measured as the average lagged absences of the class peers. We include school fixed effects to control for school-varying characteristics. In section 9 we expand on our specification by allowing for a linear trend as well as school-specific linear time trends. Cluster-robust standard errors are obtained at the classroom level as peers in the same classroom in the same year are likely to share unobservables that may affect both performance and attendance.

When estimated via OLS the above specification give a biased estimate of the effect of absences on performance due to unobserved differences across the students in their relative productivity of time spent in and out of the classroom. Unobserved differences across students in the opportunity cost of learning in class will create a bias in the OLS-estimated effect of absences on performance as part of the association between absence and performance is being explained by a differential propensity to skip class of those who at the margin have a comparative advantage in learning outside the classroom (and an absolute advantage in learning in general). The opportunity cost of learning in class depends on the relative productivity of time spent in and out of class, and may be related to ability, age, family background, and endowed resources. Out-of-class productivity in terms of learning may be age-varying. Students' cognitive gains from one year to the next depend on their endowed ability (Kuh 1995, Bandura 1994, Winne and Hadwin 1998, Pintrich 2000, Zimmerman et al. 2000, Blomeyer et al. 2008, Schack et al. 1991). To mitigate the bias from unobserved age-varying opportunity cost of learning in class we exploit exogenous variation from a one-year-only reform that relaxed the cost of missing class. Our instrument changes the cost of class attendance and helps estimate the effect of absences on performance for students who were constrained by the higher cost of missing class.

Our instrument comes from a natural experiment that took place in the school year 2009-2010 in Greece. During that school year the Hellenic Ministry of Education implemented an one-time only reform that increased the unexcused absence allowance for all students in view of the rapid spread of the H1N1 virus in Eastern Europe. The swine flu-related one-time only reform increased the number of hours students could be absent from class by 30 percent. We exclude from our analysis students who enroll into private schools in order to eschew both potential selection issues and heterogeneity in terms of the implementation of the attendance policy regulation.

An instrumental variables approach can address biases due to selection, omitted variables, and measurement error. 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. Our identification uses the one-time flu-related absences reform as an instrument for the endogenous variable *Absences*.

The first stage regression equation for our lagged value-added estimator of the returns to absences is the following:

$$\begin{aligned} Absences_{i,s,c,g,t} = & \alpha_0 + \alpha_1 FluReform_t + \alpha_2 Score_{i,g-1} + \alpha_3 X_{i,s,c,g,t} \\ & + \alpha_4 Class\ controls_c + Grade\ FE_g + School\ FE_s + \eta_{i,s,c,g,t} \end{aligned} \tag{5}$$

Where $FluReform_t = \mathbb{1}[schoolyear = 2009-2010]$. It's important to note that the Flu reform didn't increase the realized number of absences but only relaxed the students' time budget constraint allowing them to do more absences if they choose so. Thus, the coefficient δ can be viewed as the intention-to-treat effect on the treated (ITT). For all specification we cluster standard errors at the classroom lever to allow for nonzero covariance of the error term within each classroom.

Students may miss class both when they are sick and when they are not sick. In the latter case, student may miss class to enjoy leisure or study. Absence due to sickness may decrease performance. Absence for reasons other than sickness may have a non negative effect on performance depending on how the time outside the classroom is spent. We exploit a natural experiment that allowed students to miss more classes without actually being sick. The effect of absences on performance estimated comes from absences that are not related to sickness.

The validity of our empirical strategy relies on the assumption that the counterfactual trend behavior of outcome variables in treatment and control groups is the same. In other words, we require that our outcome variables do not exhibit a time-varying trend, because in that case we wouldn't be able to disentangle this trend from the time-varying treatment effect. Tables 7 and 8 show mean gpa and individual subject exam scores over time along with a 99 percent margin of error. We see that the time series of the scores remain relatively steady over time, suggesting that any effects pertaining to 2010, the year of the treatment, are not the result of a time trend.

7.1 Validity of the H1V1 virus outbreak instrument

The validity of the Flu reform as an instrumental variable relies on the assumption that it has no direct effect on treated students' performance (exogeneity assumtion). To explore how the Flu affected the treated population we provide a graph[9] that shows the number of verified H1N1 cases and H1N1-related deaths for high-school age individuals during the school year 2009-2010. We see on Figure 9 that among 209,958 students attending high school at the school year of the reform, 301 were contracted with the H1N1 strain and 2 of them died. The very few H1N1 cases in the population of high school goers appease potential worries about a direct effect of the H1N1 virus on scholastic performance.

In figure 10 we provide visual evidence of the low geographical prevalence of swine flu in the locations we collected data from. Out of the 20 prefectures sampled, five had zero or one cases of swine flu, 10 had two to five cases, 2 had between six and 10 cases, while only the prefecture of Attica, that is home to more than five million people, had 145 cases

[9] The number of all high school students in Greece is an estimate constructed as follows: For 12 and 11 graders of school year 2009-2010 we use the number of students who participated in national exams for university admission, provided by the Hellenic Ministry of Education. For the number of 10th graders of 2009-2010 we use the number of 11th graders of 2009-10. The data on H1N1 verified cases and deaths come from the Hellenic Center for Disease Control & Prevention

of swine flu in high school students. We do not exclude affected areas from our sample as the symptoms and the recovery period of the swine flu are no different from the symptoms of the common flu (Smith et al., 2009).

In addition, we provide evidence related to the timing of school absences to further appease potential concerns that the swine flu pandemic affected absences directly and not only through the relaxed class attendance policy. In figure 11 we draw mean absences per semester for the 2009-2010 school year. Although the number of new H1N1 cases in Greece started declining after October 2009 (Sypsa et al., 2011), we see that absences increased in the Spring semester of 2010 to 39 hours from 29 hours in the Fall semester. The relaxed class attendance policy was announced in April of 2010 and was put in place retroactively for both the Fall semester of 2009 and the Spring semester of 2010.

7.1.1 Placebo Tests

Our identification strategy is based on the assumption that absences react to time shocks that are related to class-attendance reforms. One may be concerned that other time-specific shocks may obscure the direct effect of changes in class-attendance regulation on absences. After reviewing all the parliamentary and regulatory activities around the 2009-swine flu pandemic, we didn't find any other reform coinciding with the change in class attendance regulation during the 2009-2010 school year or any educational reform that could potentially impact school performance during the years included in the sample. Nevertheless, it is possible that macroeconomic variables may affect both school performance and class attendance. For the change in absences to be attributed solely to the one-time-only change in class attendance regulation, one may require that mean absences returned to their pre-reform levels once the reform was removed. To appease potential concerns regarding differential time trends of absences before and after the reform in class attendance regulation, we provide visual evidence in Figure 12. We find that mean absences followed the following trajectory: Mean absences were 66.6 hours in the 2008-09 school year; 76.4 hours in 2009-10 school year (with the more lenient attendance policy); and 66.4 hours in 2010-11 school year. Although our data expand only up to 2012, we see that for two consecutive school years after the reform in class attendance regulation was abolished, mean absences returned to their pre-2010 levels, suggesting that the time trend of absences remains the same before and after the reform, and that the single peak in the time pattern of absences coincides with the class attendance reform of 2009-10.

Moreover, one may be concerned that the change in the variation of absences over time is caused by time trends and not by swine flu-related reform in class attendance regulation. Exploiting the withinschool, across-time variation of absences, we run following specification and capture the coefficients of the year dummy variables.

$$\begin{aligned} Absences_{i,s,c,g,t} = & \gamma_0 + \gamma_2 Score_{i,g-1} + \gamma_3 X_{i,s,c,g,t} + \gamma_4 Class\ controls_c \\ & + + Year\ FE_t + Grade\ FE_g + School\ FE_s + \zeta_{i,s,c,g,t} \end{aligned} \tag{6}$$

We model total hours of school absence of student i, in grade g, in school s, in year t as function of her own time-varying and time-invariant characteristics such as gender, age, age squared captured in vector $X_{i,s,c,g,t}$, and lagged Grade Point Average, grade fixed effects, school fixed effects, and year fixed effects.

Next, on Figure 13 we plot the coefficients of the dummy year variables obtained from the estimation of the above specification along with their 95 percent confidence interval obtained with clustering the standard errors at the class level. school year 2005-2006 is used a base year and is omitted from the model specification. We anticipate that the only coefficient significant in magnitude is that of the 2009-2010 year dummy variable.

The coefficients of the years 2007-2008, 2010-2011, 2011-2012[10] are not statistically significant. Although the standard errors of the 2006-2007 and 2008-2009 year dummy coefficients are quite small, the year dummy coefficients for 2006-2007, 2007-2008, 2008-2009, and 2010-2011 are roughly one fourth in magnitude of the 2009-2010 year dummy coefficient, suggesting an increase in mean absences between 9 and 13 hours in 2009-2010 in comparison to the school years spanning from 2005-2006 to 2010-2011, after controlling for student, grade, and school characteristics.

7.2 Assumptions for estimating LATE

In our study, the interpretation of LATE is the average treatment effect of those students who skipped class during the 2009-10 school year when a one-time-only relaxed attendance policy was in place, but who would not have skipped class otherwise. Nevertheless, LATE can only be identified when the instrument is exogenous, when we have a valid first stage, when the exclusion restriction is satisfied, and when the monotonicity assumption is met

[10]Our data contain 860 observations for 2011-2012, while we have 19,101; 20,027; 21,567; 18,178; 14,120 observations for 2005-2006; 2006-2007; 2007-2008; 2008-2009; 2009-2010; 2010-2011 respectively. Small sample size for 2011-2012 may result in statistical power issues when it comes to the statistical significance of the 2012 year dummy.

(Imbens and Angrist, 1994). The exogeneity assumption is met because the students do not control their year of birth, and, consequently, they cannot control the timing of their school enrollment. The validity of the first stage and the rejection of the weak-instrument problem are shown in the next section. For the exclusion restriction to be met, we need to establish that the instrument (namely the new relaxed class attendance policy) does not affect grades directly other than through absences. The new attendance policy was introduced immediately after a swine flu pandemic in Europe. To address any concerns regarding the direct effect of the instrument on grades, we use data on flu cases to show that, in fact, very few students contracted flu during the 2009-10 school year. Next we explain why the monotonicity assumption is met. Following Imbens (2010, p.415), imagine a model where the grade of student i solely depends upon his absences as follows:

$$S_i = \alpha_o + \alpha_1 A_t + \epsilon_i \tag{7}$$

Absences are endogenous ($cov[A_t + \epsilon_i] \neq 0$), due to personality traits or parental monitoring correlating both with absences and scores. Now, one can think of an absence not as a binary random variable, but as a continuous latent variable (A_t^*) which describes the student's utility of skipping class. Next, this latent variable can be modeled as follows:

$$A_i^* = \beta_o + \beta_1 D_i + \upsilon_i \tag{8}$$

Where D_i reflects the assignment to the relaxed class-attendance policy. The continuous variable A_t^* is mapped into a binary variable by the following:

$$A_i = \begin{cases} 1, & \text{if } A_i^* \geq 0 \\ 0, & \text{if } A_i^* < 0 \end{cases} \tag{9}$$

The inclusion of D_i in the equation above reflects the benefit of being absent from class. That is, if $D_i = 1$, the utility of being absent from class is higher, since you are free to invest your time the way you want. Hence, a rational utility-maximizing agent would set β_1 higher than 0. Other characteristics such as lack of motivation remain in the error term υ_i. Unmotivated students won't go to class, even if $D_i = 0$: $\upsilon_i \geq -\beta_0$. They are the always takers. Very motivated students will go to class, even if $D_i = 1$: $\upsilon_i < -\beta_0 - \beta_1$. They are the never takers. The estimated results come from the compliers, who are defined as: $-\beta_0 > \upsilon_i \geq -\beta_0 - \beta_1$. This framework excludes the existence of defiers, since (i) if an individual is absent if $D_i = 0$, this implies they will also be absent if $D_i = 1$ (if $\upsilon_i \geq -\beta_0$, then $\upsilon_i \geq -\beta_0 - \beta_1$) and (ii) if an individual is present if $D_i = 1$, this implies they will also be present if $D_i = 0$ (if $\upsilon_i < -\beta_0 - \beta_1$, then $\upsilon_i < -\beta_0 - \beta_1$, then $\upsilon_i < -\beta_0$). Therefore, we are able to identify a well-defined local average treatment effect.

To see why the IV estimate of the second stage (α_1) does not equal ATE, we switch to a heterogeneous framework. This means that the parameters potentially differ by individual, so formally we have α_{1i} in the first-stage regression. If absences were exogenous in the first place, we would still be able to measure an ATE(T), since $ATE(T) = E[G_i|A_i = 1] - E[G_i|A_i = 0] = E[\alpha_{1i}] = \frac{1}{n}\sum_{i=1}^{n} \alpha_{1i} = \bar{\alpha_1}$. Since A_i is exogenous, this average can still be interpreted as an ATE(T). Now consider A_i as an endogenous variable and one used 2SLS in order to get a constant estimate. In a heterogeneous framework, the 2SLS estimator is as follows:

$$\alpha_{1,2sls} = \frac{cov[G_i, D_i]}{cov[A_i, D_i]} = \frac{\frac{1}{n} sum_{i=1}^{n} \alpha_{1i}\beta_{1i}}{\frac{1}{n} sum_{i=1}^{n} \beta_{1i}} \tag{10}$$

This boils down to ATE(T) if and only if $\alpha_{1i} = \alpha_1 \forall i$ and/or $\beta_{1i} = \beta_1 \forall i$. Therefore, in a heterogeneous framework the 2sls estimator equals a weighted average of individuals' treatment effects, with largest weight for whom the instrumental variable is most influential. Under the assumptions mentioned above the weighted average measures a LATE. This exercise makes clear that homogeneity in the first stage means LATE equals ATE. Thus, to characterize the LATE, we do the following. We rerun the first stage and include interaction effects between D_i and observables to find for which individuals i, β_{1i} is large or small. Equation 10 makes clear that individuals with a large β_{1i} contribute to the LATE estimator and individuals with a small β_{1i} do not contribute to the LATE estimator [11]. Whereas the monotonicity assumption is also fundamentally untestable, we would not want the total effect of D_i to become negative. Indeed, this would cause the explanation below equation 9 to break done, since β_{1i} is not positive for all individuals.

8 Main Results

8.1 Effect of Performance

Main results are reported on Table 4. The first column in Table 4 corresponds to the contemporaneous specification without lagged score and without school and year fixed effects. The unit of absences is in tens of hours. This shows that missing ten additional hours

[11] In the extreme where $\beta_{1i} = 0$ the contribution of student i is zero

of class, a student's grade point average decreases by 6.5 percent of a standard deviation, ceteris paribus. In column (2) in Table 4 we expand on the contemporaneous specification by including the student's grade point average in the previous year. Controlling for lagged score allows us to capture both innate ability as well as the history of all inputs included in the educational production function up to the current period. When we control for lagged performance, we see that the effect of absences on performance becomes less negative, indicating that past performance explains some portion of the association between absences and performance. In other words, higher levels of past performance may be associated with both higher attendance and higher performance. We find that missing ten hours of class decreases one's performance by 2.2 percent of a standard deviation on average.

In column (3), which corresponds to specification 4, we include school fixed effect in our value-added specification to control for school-specific patterns of performance. We see that our estimates don't differ much from column (2): a ten-unit increase in the number of hours of class missed decreases a student's performance by 2 percent of a standard deviation.

Our estimates of column (3) are subject to an omitted-variable bias as unobserved grade-specific shocks may be associated with lower rates of attendance and poorer performance. For example, some students may be afflicted with sickness in certain years but not others. When a student is sick, it is probable that they exhibit lower performance as well as lower class attendance. Moreover, not everyone is affected by such time-specific shocks in the same time periods. Nevertheless, when these time-specific shocks occur and are not observed, we cannot disentangle their effect on performance from the effect of absences on performance, as we do not observe who was subject to such a shock and who wasn't. There are additional grade-specific factors that could bias the effect of absences on performance. Students may become better at learning on their own as their grow up. It's important to note that our analysis looks at students who are at the end of their adolescence and near the beginning of their adulthood. Students who get closer to the age of 18 may have accumulated enough human capital, so as to substitute sufficiently class learning with self learning. The existing literature (see, Kuh 1995, Bandura 1994, Winne and Hadwin 1998) supports that college aged individuals are more able to learn on their own in comparison to younger students. Therefore, as students reach the end of their secondary education and prepare for their university entrance exams, they may find it more productive to learn on their own rather than in class. This effect is time-specific as it is more relevant to students in the junior or senior year of high school. However, the extent to which age brings upon a certain student the necessary self-discipline and maturity to learn on their own is largely idiosyncratic and differs from person to person. In that sense, our omitted-variable bias comes from a combination of grade and individual -specific unobservables.

To mitigate the omitted-variable bias from grade-student-specific shocks we exploit variation in the class attendance regulation. During the 2009-2010 school year students were allowed to miss 30 percent more classes without penalty. The relaxed attendance policy allowed students to miss class for reasons different from those related to sickness. As students could miss class without providing a doctor's note or their parent's approval, students could miss class to enjoy more leisure or study. The reform allows us to compare same grade individuals across years, while controlling for their past performance, to net out any unobserved grade-student-specific unobserved shocks. Our estimates are reported in column (4) of Table 4 and correspond to specification 4 estimated with IV. We find that missing ten hours of class increases the grade point average by 4.1 percent for those students who missed more classes due to the relaxed attendance policy. Since the new attendance policy didn't force students to miss class but rather simply gave the opportunity to miss class more frequently, only students who would be better off either in terms of leisure of studying at home would take advantage of the new policy. Exploiting the relaxed attendance policy to enjoy more leisure or to study at home would generate in principle different returns to absences. We do not know how students actually allocated their out-of-class time. However, we can interact students, class, and school characteristics with the variable of interest and estimate heterogeneous effects of absences. Our reduced form and first stage estimates are reported on Table 5. We find that the relaxing the class attendance policy results in a roughly 11 hour increase in the number of hours of class missed in a given year. Our reduced form results show that the reform that changed the attendance requirements induced a 4.6 percent of a standard deviation increase in the grade point average.

8.1.1 Robustness

One threat to identification is the existence of upward trend that could explain the positive estimated effects of absences on performance. To control for the existence of time trends in our outcome variables we perform the following robustness checks: We augment our specifications by adding a linear time trend or school-specific linear trends. In the case of a linear time trend our main specification 4 becomes:

$$\begin{aligned} Score_{i,s,c,g,t} =& \beta_0 + \beta_1 Absences_{i,s,c,g,t} + \beta_2 Score_{i,g-1} + \beta_3 X_{i,s,c,g,t} + \beta_4 t \\ &+ \beta_5 Class\ controls_c + Grade\ FE_g + School\ FE_s + \epsilon_{i,s,c,g,t} \end{aligned} \tag{11}$$

where the parameter β_4 captures the effect time t on our outcome variables. We go one step further by allowing for the existence of school-specific linear trends in our outcome variables. In that case, our main specification 4 becomes as follows:

$$\begin{aligned} Score_{i,s,c,g,t} =& \beta_0 + \beta_1 Absences_{i,s,c,g,t} + \beta_2 Score_{i,g-1} + \beta_3 X_{i,s,c,g,t} + \beta_4 t_s \\ &+ \beta_5 Class\ controls_c + Grade\ FE_g + School\ FE_s + \epsilon_{i,s,c,g,t} \end{aligned} \tag{12}$$

where the effect of time t_s on performance is now allowed to vary from one school to the next. Both specifications 11 and 12 are estimated via IV using exogenous variation from the introduction of a relaxed attendance policy.

Our results are shown in Table 6. We see that although our estimates of the returns to class absences decrease in magnitude compared to Table 4, the estimated standard errors remain almost half the size of the effects of absences both in odd-numbered columns that include a linear time trend as an additional control, and in even-numbered columns where school-specific time trends have been included to the list of explanatory variables. Our estimated effects are smaller compared to the specifications without the time trends in Table 4, suggesting the existence of some time trends. Nevertheless, when we control for even school-specific time trends, the effect of absences on performance is found positive and significant both in magnitude and statistically. Specifically, our preferred specification shown in column (8) of Table 6 shows that a ten-hour increase in the class absences leads to an increase of school performance by 2 percent of a standard deviation.

8.2 Heterogeneous propensity to skip class

8.3 By Ability

The H1N1-related reform relaxed for one school year only the class attendance policy. The reform allowed students to skip up to 34 more hours of school without penalty. Nevertheless, the decision to skip class when given the opportunity may not be identical for everyone. In fact, individual propensity to skip class may depend on individual, class or school characteristics. In this section we explore whether there is differential response to the relaxed time-budget constraint.

The first question we ask is: Does the effect of the flu shock on absences differ across the ability distribution? To answer this question, we employ the following regression model with interaction terms. The model below is an augmented version of regression equation (1) where the flu-shock variable is interacted with a prior-ability variable. To proxy cognitive ability we obtain the student's within-school rank based on the 10th grade GPA. The *Ability* variable takes the values in [1,100] where the value 100 represents the top 1 percent of one's class. The following model is estimated for students attending 11th grade or 12th grade across years.

$$\begin{aligned} Absences_{i,s,c,g,t} =& \alpha_0 + \alpha_1 Flu_t + \alpha_2 Flu_t \times Ability_{i,10} + \alpha_3 Ability_{i,10} + \alpha_4 X_{i,s,c,g,t} \\ & + \alpha_5 Class\ controls_c + Grade\ FE_g + School\ FE_s + \eta_{i,s,c,g,t} \end{aligned} \tag{13}$$

We hypothesize that when the class attendance policy relaxes student who have the resources or the ability to learn outside the classroom may choose to skip class. Among those students we expect that students with higher human capital accumulation or ability may exploit the relaxed attendance regulation even more. Our findings are presented in table 8. We find that the higher the measure of prior cognitive ability the more the hours a student skips class. In particular we find that when controlling for variation across students and grade, being ranked 1 percent higher in your class increases the effect of a relaxed class attendance policy on your hours of absences by almost 2 hours. However, our estimated effect has large standard error. When we focus on different types of absences, we find that being ranked 1 percent higher in your class increases the estimated effect of a relaxed class attendance policy on your hours of excused absences by more than 2 hours, with a standard error almost half the size. The effect of the lax attendance policy on unexcused absences does not seem to vary with prior ability as the estimated coefficient of the interaction of interest is not significant quantitatively and statistically.

8.4 By Peer Quality

Next, we examine how the effect of the relaxed attendance policy on absences changes with the mean performance of classroom peers. Peer quality is defined as the average of lagged

Grade Point Average of class peers[12]. Since we are employing a within-school estimation approach, the peer quality variable would pick up differences in the peer quality across classes and across years within the same school. We are using a logarithmic transformation of one's peer quality to normalize those differences and to estimate the effect of relative rather than absolute changes in the peer quality. We model differential effects of the flu shock on absences by peer quality using the following specification.

$$\begin{aligned} Absences_{i,s,c,g,t} = &\alpha_0 + \alpha_1 Flu_t + \alpha_2 Flu_t \times Log(PeerQuality)_c + \alpha_3 Log(PeerQuality)_c \\ &+ \alpha_4 Score_{i,g-1} + \alpha_5 X_{i,s,c,g,t} + \alpha_5 Class\ controls_c + Grade\ FE_g \\ &+ School\ FE_s + \eta_{i,s,c,g,t} \end{aligned} \tag{14}$$

Where *Class Engagement* is the average lagged absences of class peers. Our OLS estimates of the equation 14 reported in table 9 show that on average peer quality matters significantly for the effect of the flu shock on absences. Specifically, a 10 percent decrease in peer quality leads to a one and a half-hour increase in the effect of the relaxed attendance policy on mean total absences. When we split absences in excused and unexcused we see that peer quality matters for the effect of the relaxed attendance policy only on excused absences, that is whole day absence for which the doctor's note or a parent's approval was provided. In particular, a 10 percent decrease in peer quality leads to a almost one and a half-hour increase in the effect of the relaxed attendance policy on mean excused absences, with a standard error of two fifths of that size. Peer quality doesn't seem to matter for the effect of the relaxed attendance policy on performance, as the estimated coefficient of the interaction of peer quality with the shock is not significant either in magnitude or statistically. Considering that the relaxed attendance policy is more likely to be exploited by those students who can learn outside the classroom, the estimated differential effect of the flu reform by peer quality measures the negative externality such a student incurs when they are forced to stay in a deteriorating class environment.

8.5 By Postcode Income

Next, we are interested in measuring potential differential effects of the flu-related reform on absences by socioeconomic status. Although we do not observe students' family income, we

[12] We follow the so-called leave-one-out approach in defining peer quality. For each student we calculate the average lagged GPA of the other students in the same classroom.

have a measure of mean family income at the postcode level. We are interested in the cross-sectional variation of income rather than the over-time variation for two reasons. The flu reform is a variable that changes over time, and in order to measure its heterogeneous effects in terms of cross-sectional characteristics, we can't have those characteristics changing over time as well; if this were the case, we wouldn't be able to completely exclude the possibility of that part of the variation in our cross- sectional characteristics could be explained by our instrument. Thus, as a measure of socioeconomic status, we use the mean family income at the postcode level expressed in euros in 2009, a year before the flu-related reform. We explore differential propensity to skip class in terms of socioeconomic status setting using the following model:

$$\begin{aligned} Absences_{i,s,c,g,t} = & \alpha_0 + \alpha_1 Flu_t + \alpha_2 Flu_t \times Log(Income)_s + \alpha_3 Log(Income)_s \\ & + \alpha_4 Score_{i,g-1} + \alpha_5 X_{i,s,c,g,t} + \alpha_5 Class\ controls_c + Grade\ FE_g \\ & + School\ FE_s + \eta_{i,s,c,g,t} \end{aligned} \tag{15}$$

According to table 10 a 10 percent decrease in family income increases absences by almost 10 hours on average when under the relaxed attendance policy. This evidence suggests that the better socioeconomic conditions negatively correlated with skipping class. We propose two hypotheses that may explain our evidence; these mechanisms are not mutually exclusive. First, students of higher family socioeconomic status (as proxied by the mean postcode income) may be less prone to the absenteeism not necessarily because it is not in their best interest to skip class but perhaps because social norms and behaviors they have been exposed to may deem such a behavior as immoral or unacceptable. Second, public schools in wealthier neighborhoods may provide higher-quality schooling in terms of either the educational inputs or the learning environment. Nevertheless, our results are robust to controlling for peer quality. As previously noted, the ministry of Education does not take into consideration any quality characteristics when allocating teachers to schools; however, self-selection cannot be excluded.

8.6 Heterogeneous Returns to Absences

8.7 By Ability

Next, we investigate whether and how returns to absences vary across the ability distribution. It is important to note that the estimated returns to absences that we have discussed so far are relevant to those who choose to miss class due to the newly introduced lax attendance policy. Assuming that only students who would benefit from class absence who choose to skip class, we anticipate an average return to class absence higher than zero, even though the magnitude of the return to absence may vary across the ability distribution. Using within-cohort ranking in the 10th grade to proxy cognitive ability, we estimate the effect of absences on performance due to the introduction of a relaxed attendance policy conditional on cognitive ability. We employ the following specification:

$$\begin{aligned} Score_{i,s,c,g,t} =& \alpha_0 + \alpha_1 Absences_{i,s,c,g,t} + \alpha_2 Absences_{i,s,c,g,t} \times Ability_{i,10} + \alpha_3 Ability_{i,10} \\ &+ \alpha_4 X_{i,s,c,g,t} + \alpha_5 Class\ controls_c + Grade\ FE_g + School\ FE_s + \eta_{i,s,c,g,t} \end{aligned} \tag{16}$$

where $g \in 11, 12$. Specification 16 is estimated by IV. The two endogenous variables-absences and the interaction of absences and our proxy for cognitive ability-are instrumented by the flu shock and the interaction of the flu shock and our proxy for cognitive ability, respectively. Our results are shown in Table 11. We find that the higher a student's prior performance, the more positive the effect of absences of school performance. In particular, the performance of a student at the top one percent of his cohort improves by a net almost 0.2 percent of a standard deviation when he misses additional 10 hours of class in a given year. Our findings suggest that students who exhibit higher cognitive ability are worse off staying in class compared to less able students. Our results are opposite for student at the left end of the ability distribution. The performance of students at the bottom 1 percent of their cohort decreases by a net 0.2 percent of a standard deviation when they miss additional 10 hours of class in a given year.

Our evidence suggests that students of different cognitive ability either exploit differently the relaxed attendance policy or their out-of-class learning productivity is not homogeneous. The strong positive returns to absences for more able students suggest that better students may choose to skip class in order to study or avoid some class externality that could possibly disrupt their learning process. On the other hand, the negative returns to absences for weaker students implies that their out-of-class productivity is not higher than their in-class productivity either because weaker students may spend their out-of-class time in leisure or because they do not have enough human capital accumulation in order to harvest the same gains from self-study as better students do.

8.8 By Peer Quality

To see how returns to absences differ across the peer quality distribution we estimate the following model where we interact the effect of absences with the natural logarithm peer quality. Peer quality is calculated for each student as the average lagged GPA of other peers in the same classroom.

$$\begin{aligned} Score_{i,s,c,g,t} =& \alpha_0 + \alpha_1 Absences_{i,s,c,g,t} + \alpha_2 Absences_{i,s,c,g,t} \times Log(PeerQuality)_c \\ &+ \alpha_3 Log(PeerQuality)_c + \alpha_4 Score_{i,g-1} + \alpha_5 X_{i,s,c,g,t} + \alpha_5 Class\ controls_c \\ &+ Grade\ FE_g + School\ FE_s + \eta_{i,s,c,g,t} \end{aligned} \tag{17}$$

Our estimates are shown on Table 12. Overall, having class peers at the top quintile of the sample distribution increases your return to absence in terms of GPA, suggesting that high achieving peers may intimidate a student or the instructor neglects weaker students. However, the estimated standard error of the interaction term of interest is much larger than the coefficient, suggesting that that the effect of absences on performance does not vary statistically significantly by peer quality. It is important to note that the variation we observe in the peer quality in the classroom is not large. The difference in the mean peer quality between the top and bottom quintile is 16.58%, where peer quality is defined as the mean lagged GPA of one's class peers.

8.9 By Postcode Income

We explore differential effects of absences on performance by estimating model (18).

$$\begin{aligned} Score_{i,s,c,g,t} =& \alpha_0 + \alpha_1 Absences_{i,s,c,g,t} + \alpha_2 Absences_{i,s,c,g,t} \times Log(Income)_s \\ &+ \alpha_3 Log(Income)_s + \alpha_4 Score_{i,g-1} + \alpha_5 X_{i,s,c,g,t} + \alpha_5 Class\ controls_c \\ &+ Grade\ FE_g + School\ FE_s + \eta_{i,s,c,g,t} \end{aligned} \tag{18}$$

Our results in Table 13 show postcode income does not seem to matter quantitatively or statistically for the effect of absences on performance.

8.10 By Subjects

In this section we explore how returns to absences differ among different subjects. We focus our analysis on Modern Greek, and Mathematics. Both subjects belong to the core curriculum and are mandatory courses for every high school student. It is important to note that we do not observe in our data how many hours of classes each student missed for every subject in a given school year. We rather observe an aggregate number of hours of absences for every student in a given school year. We investigate the effect of the total number of absences a student makes in a given school year on the end-of-the-year cumulative exam scores for Greek and Mathematics. Exams scores are not curved a follow a 100-unit scale. We standardize the exam scores by school and grade. Our specification is that described in equation 4 and is estimated by IV. The outcome variable *Score* takes the values of standardized exam scores in Greek, and Mathematics. Our results are shown in Table 14. We find that the level of Absences does not have a statistically significant effect on the exam score in Greek. However, our estimates show that there are positive and statistically significant effects of Absences on the exam score for Mathematics, suggesting that missing more hours of class improve the Mathematics exam score. Specifically, missing additional 10 hours of class improves the Mathematics exam score by roughly 3 percent of a standard deviation. Our estimates are robust when we include school-specific linear time trends, shown in column (4) of Table 14.

8.11 By Track

In this section we explore how returns to absences vary across different specializations. We have already mentioned that students in the 11th and 12th grade choose a field of specialization (track): classics, information technology, or science. Attending a specific track allows students to apply for admission to university degree programs relevant to the chosen track. For instance, in order to apply to university degree program in History and Archaeology one must have attended the Classics track in high school. We use the subsample (18,943 individuals) of 11th and 12th grade students for whom we have full specialization information, final exam scores in the track courses, and attendance information to investigate heterogeneous returns to class absences for the three tracks available. We estimate the following specification via IV, where the endogenous variable absences is instrumented by the exogenous reform in the class attendance policy during the 2009-10 school year.

$$\begin{aligned} Score_{i,s,c,g,t} =& \beta_0 + \beta_1 Absences_{i,s,c,g,t} + \beta_2 Score_{i,g-1} + \beta_3 X_{i,s,c,g,t} \\ &+ \beta_4 Class\ controls_c + School\ FE_s + \epsilon_{i,s,c,g,t} \end{aligned} \tag{19}$$

The difference between specification 19 and specification 4 is that in specification 19 we cannot include grade-specific fixed effects. Therefore specification 19 is estimated for 12th grade students using lagged score values from the 11th grade as a control variable.

Our results are shown in Table 15. We find that absences have a significant effect on performance both quantitatively and statistically for students in the Information Technology (IT) and Science Track. The effect of absences on performance for students attending the Classics is found to be negative, suggesting that missing more hours of class decreases the average score in the track courses for students specializing in Classics. On the other hand, missing more hours of class seems to improve the performance in terms of the average score in the track courses for students attending the IT or the Science Track, who missed more classes due to the relaxed attendance policy.

9 Conclusion

Our study uses new high school transcript data to address two questions. First, why does a student skip class? Second, what is the effect of absences on performance? Our identification strategy exploits a natural experiment that occurred when a European outbreak of swine flu led Greek officials to adopt regulations allowing students to miss 30 percent more class time without penalty during the 2009-20 school year. We provide evidence that very few students were directly affected by the swine flu; high school students were not a high-risk group, and most student absences took place well after the outbreak ended. Our institutional setting has the following features. First, students are assigned to classes according to the alphabetical order of their surnames, and class peers remain the same across subjects. Second, assignment to schools follows a school- district system based on geography. Third, attendance is diligently monitored, and the penalty for missing more than 114 class hours in a given year is severe: grade retention. The one-time-only reform allowed students to skip one period or a whole day of school. We use a within-student estimator to control for individual and age effects. Our outcomes include grade point average in the 10th, 11th, and 12th grades, and exam scores in specific subjects with minimal curricular variation across classes and schools.

We show that, when given the opportunity, students who are more likely to skip classes are those who have established records of higher prior performance, who have academically weaker peers in their classes, or who live in poorer neighborhoods. We find that students who choose to skip class when the attendance policy relaxes perform better, achieving an overall GPA that is 0.04 of standard deviation higher. We explore how the introduction of a relaxed attendance policy affected students in different parts of the ability distribution. We find that students of higher prior ability enjoy higher returns to absences, suggesting that more able students can do better under a less strict attendance policy. Students at the top one percent of the ability distribution proxied by the 10th grade GPA enjoy a net two percent of standard deviation increase in their end-of-the-year exam performance when they miss additional 10 hours of class. Our results are opposite for weaker students. The performance of students at the bottom one percent of their cohort, as measured in the 10th grade, decreases by two percent of a standard deviation when they miss additional 10 hours of class.

We also explore heterogeneous returns to absences across both different subjects in the core curriculum as well as across different specialization tracks in the 11th and 12th grade. We find negative returns to absences in Greek language and positive returns to absences in mathematics in the core curriculum. Our results are similar in the specialization track analysis, where we find negative and statistically insignificant returns to absences for students in the Classics Track, but positive returns for students in the Information Technology and Science Tracks, which both put emphasis on mathematics in the track curriculum. Our finding suggest that it is possible to gain from absence in certain fields of study but not in others.

Our estimated positive effects of absences show that a compulsory class attendance policy can hurt the performance of certain students. Allowing students to miss class has considerable effects on their performance. Our effect is of comparable magnitude to being taught by a teacher one standard deviation above the average (Chetty et al. 2014, Rivkin et al. 2005b). Moreover, our effect on test scores is of a similar magnitude to reducing the class size by 10-15 percent (Krueger 1997, Angrist and Lavy 1999). These interventions are significantly more costly than a lax attendance policy and it could free up resources that could be used to boost the performance of those who rely more on school resources.

One limitation of our study is that we do not observe class attendance for specific subjects, and thus we cannot exclude the possibility that the observed differences in returns to absences may be due to the students' selecting to skip specific subjects but attend others. Our findings speak both to literature exploring the reasons for absenteeism as well as the literature investigating the quantity of inputs in the educational production function. A revealed preference argument leads us to claim that those who exploit a relaxed attendance policy do so because it makes them happier, either because they can enjoy more leisure or because they can learn on their own. Our estimated return to absence can be viewed as the externality compliers incur when they are forced to attend class. This externality may be related to class size, peer quality, and/or school characteristics. Our study supports the view that students of different characteristics have different input needs, and it highlights the trade-off between equality in an educational system and efficiency in terms of allocation of educational inputs.

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Table 1: Upper limits of school absences

	Old Regulation	**Flu Regulation**
Excused Absences	64	83
Unexcused Absences	50	65
Total Hours	114	148

Figure 1: A Model of Time Allocation

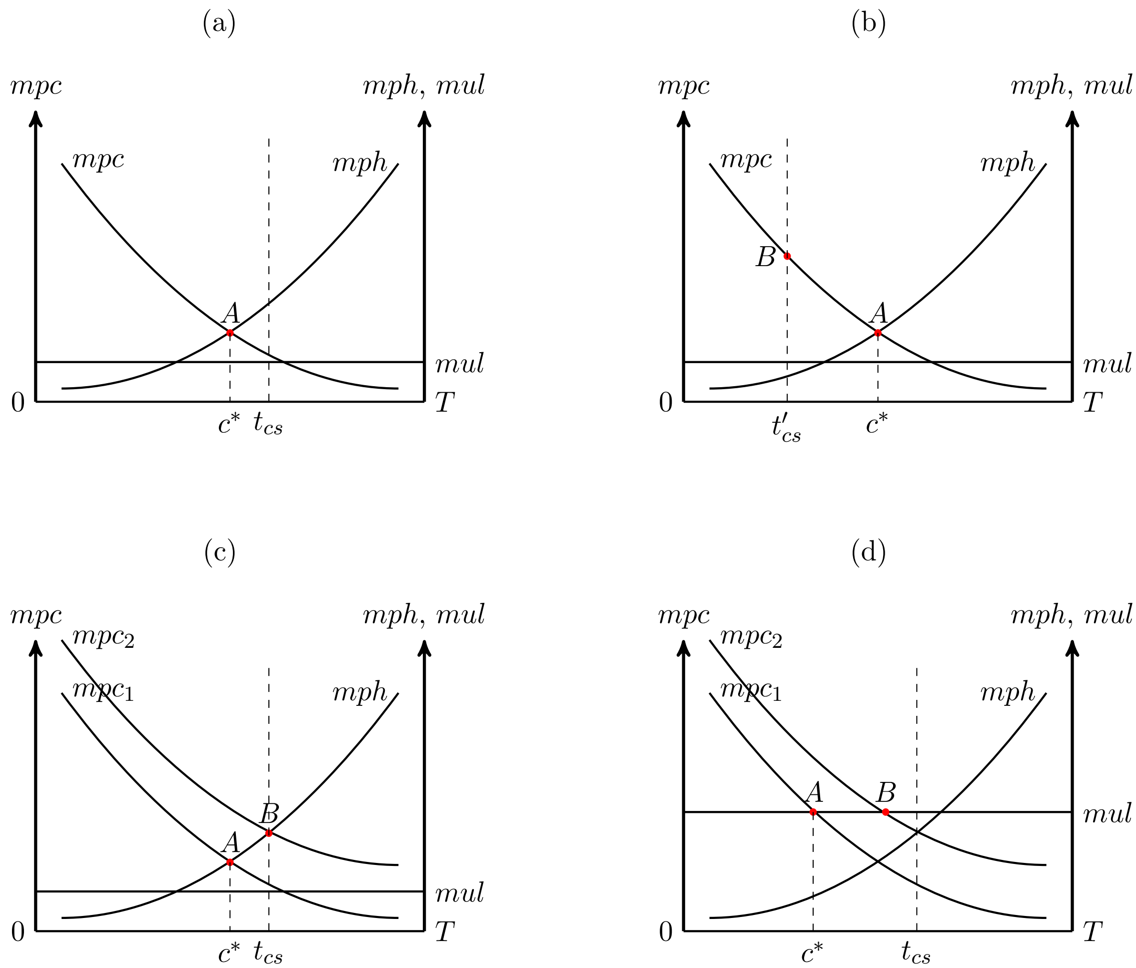

Figure 2: New Transcript Data

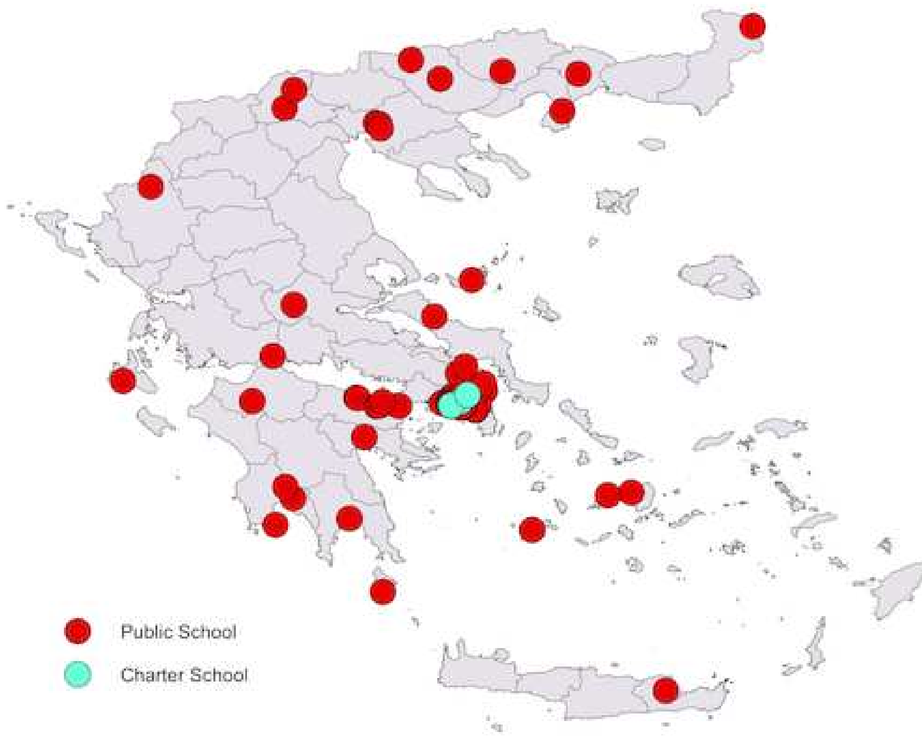

Table 2: Average Number of Absences

	Total Absences		Excused Absences		Unexcused Absences	
	Mean	s.d.	Mean	s.d.	Mean	s.d.
Average	59.13	63.47	25.02	24.03	34.09	57.35
Math Score						
Highest Quintile	60.06	32.92	31.68	26.40	28.36	13.99
Fourth Quintile	58.46	31.60	28.42	24.40	30.04	14.33
Third Quintile	60.75	30.91	28.45	24.01	32.25	14.09
Second Quintile	64.94	30.33	29.85	23.78	35.03	13.83
Lowest Quintile	88.77	83.91	32.31	25.41	56.47	82.93
Gender						
Male	66.16	29.18	23.68	22.76	36.95	35.59
Female	65.71	42.71	31.90	25.51	33.78	32.23
Grade						
10th	53.69	55.55	19.42	19.79	34.29	51.13
11th	61.79	52.91	23.29	21.50	38.40	47.80
12th	83.36	36.34	45.34	24.02	38.03	27.72
Semester						
Fall	26.50	28.43	9.48	13.63	17.02	23.10
Spring	35.49	28.85	18.26	18.35	17.23	21.03
Setting						
Urban	65.01	43.33	31.57	27.29	33.50	32.74
Rural	66.98	50.62	29.78	24.63	37.17	43.58
Neighborhood Income						
Highest Quintile	68.19	58.10	29.41	24.28	38.48	52.90
Fourth Quintile	66.22	44.80	30.56	25.50	35.77	35.51
Third Quintile	67.83	48.16	30.49	24.47	37.34	39.87
Second Quintile	63.84	45.02	28.15	23.67	35.70	36.71
Lowest Quintile	68.38	54.75	30.51	25.53	37.88	48.97
Peer Quality						
Highest Quintile	66.40	31.54	31.67	25.01	34.55	15.37
Fourth Quintile	69.31	32.00	34.36	25.41	34.67	15.49
Third Quintile	69.88	31.65	34.54	25.54	35.13	14.97
Second Quintile	71.72	32.49	35.92	25.06	35.77	17.58
Lowest Quintile	72.53	32.25	36.57	24.72	35.97	17.07
Year						
2006	62.47	51.68	26.24	22.44	36.22	45.86
2007	66.37	52.53	28.96	24.16	37.41	46.09
2008	63.22	47.80	27.53	24.13	35.71	40.49
2009	66.92	50.35	30.15	24.44	36.53	44.27
2010	76.42	49.78	35.56	27.84	40.89	40.20
2011	66.42	46.81	31.39	24.17	35.06	39.42
2012	65.30	59.96	32.99	27.39	33.81	53.13

Sample: 58,923 obs; 19,641 individuals. Neighborhood income is measured as average family income at postcode in Euros in 2009. Peer quality is the mean lagged grade point average of class peers

Figure 3: Distribution of Total Absences under Old Attendance Regulation

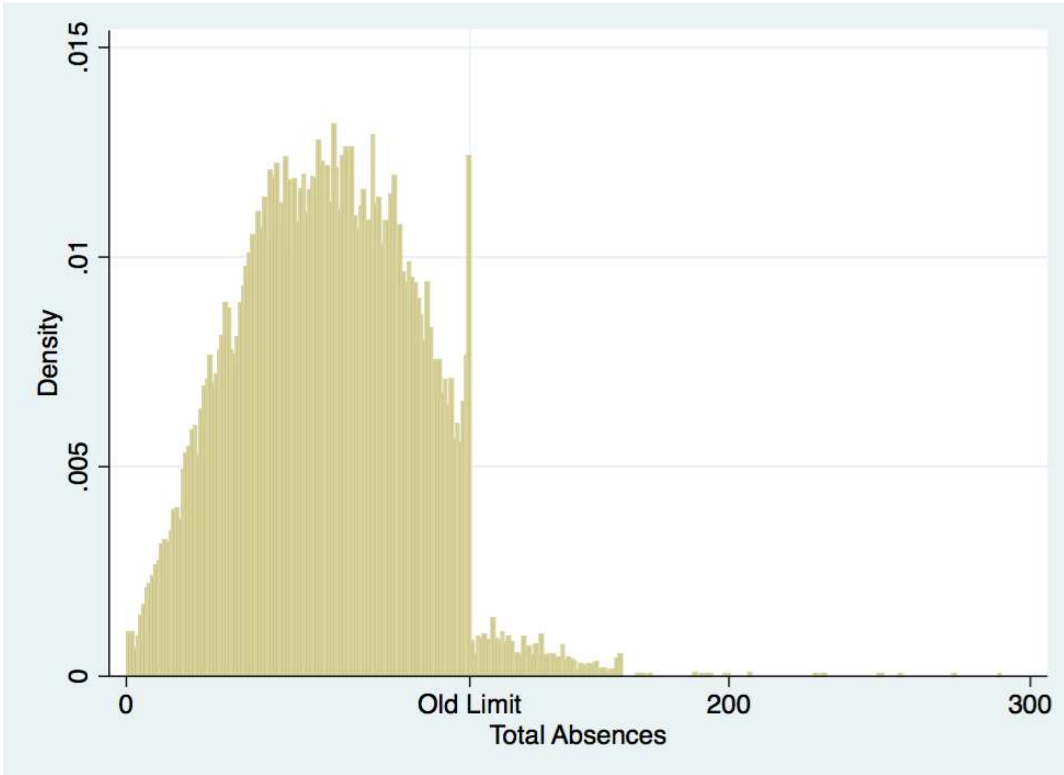

Figure 4: Distribution of Total Absences under New Attendance Regulation

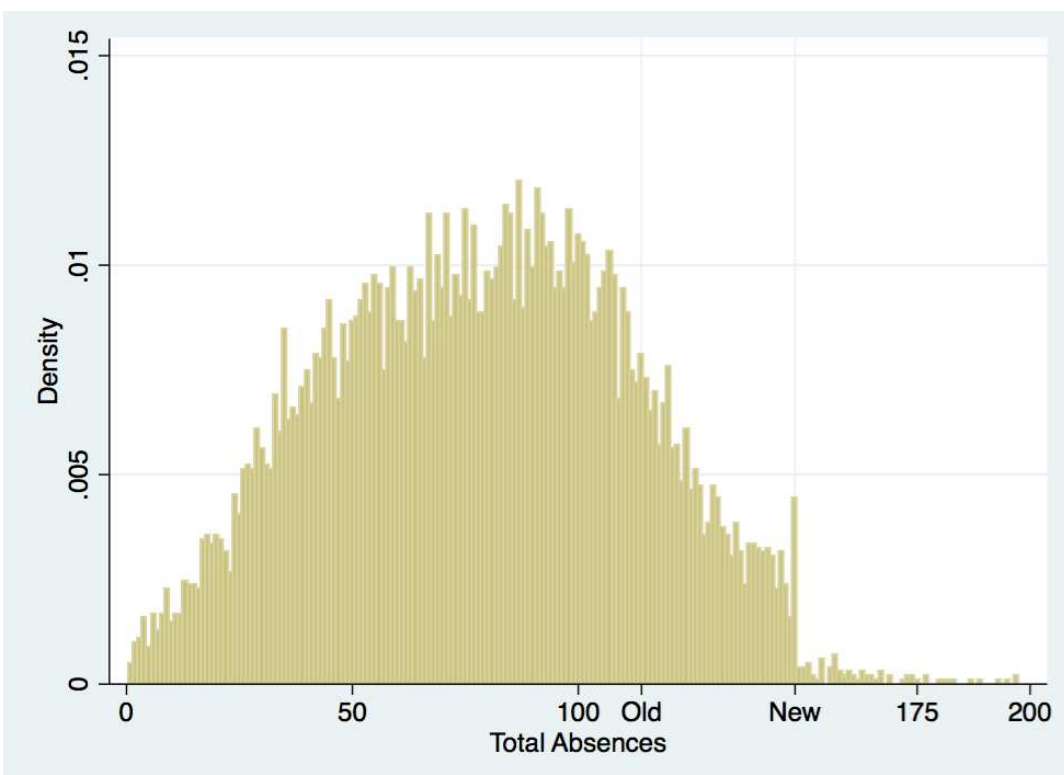

Figure 5: Distribution of Unexcused Absences under Old Attendance Regulation

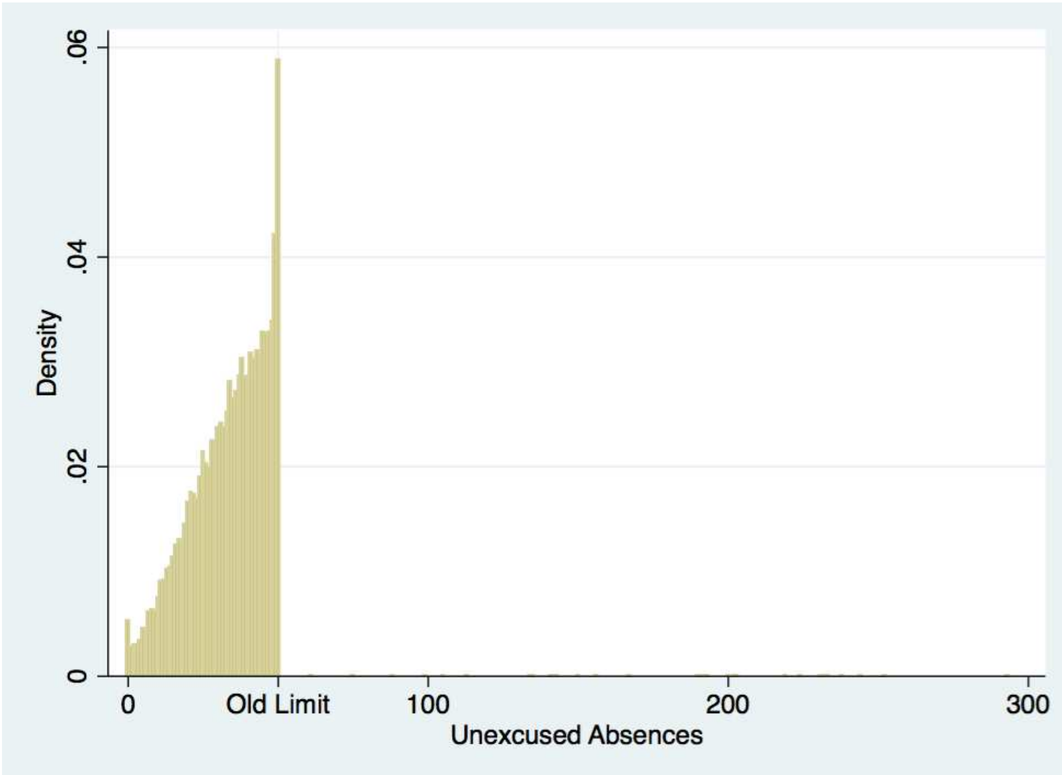

Figure 6: Distribution of Unexcused Absences under New Attendance Regulation

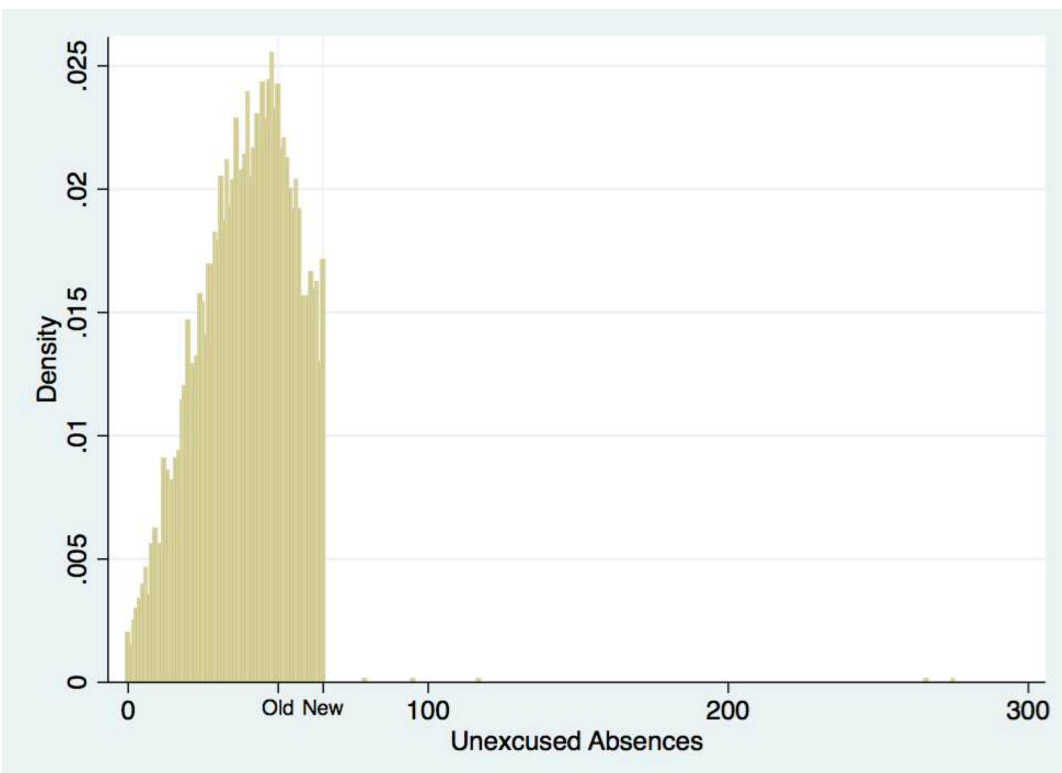

Table 3: Treatment and Control Group

Variable	Control Mean	Treatment Mean	Difference (b/s.e.)
Student Characteristics			
Age	16.928	17.530	0.602***
			(0.008)
Female	0.558	0.558	0.000
			(0.005)
# of Students	48,528	10,395	
Class Characteristics			
Class Size	22.908	22.296	-0.612***
			(0.038)
Mean Lagged GPA	13.769	13.733	-0.036**
			(0.13)
# of Classes	2,508	534	
School Postcode Characteristics			
Rural	0.060	0.058	-0.002
			(0.003)
log(Population)	11.109	11.103	-0.006
			(0.011)
log(Income)	9.967	9.964	-0.003
			(0.002)
# of Schools	85	83	

Note: Data span graduating classes of 2008-2012 (years 2006-2012). Sample: 58,923 obs (19,641 individuals). Annual Income is in 2009 Euro. We use data from 12 schools in rural areas and 73 in urban areas. Grades use a 20-point scale. Population refers to city population or the population of the smallest unit of area obtained from the 2011 Census. The treatment period is the year 2010 while the control period consists of the pooled years 2006, 2007, 2008, 2009, 2011, 2012. *,**,*** denotes significance at the 10%,5% and 1% level respectively.

Figure 7: No Trend Assumption

Figure 8: No Trend Assumption

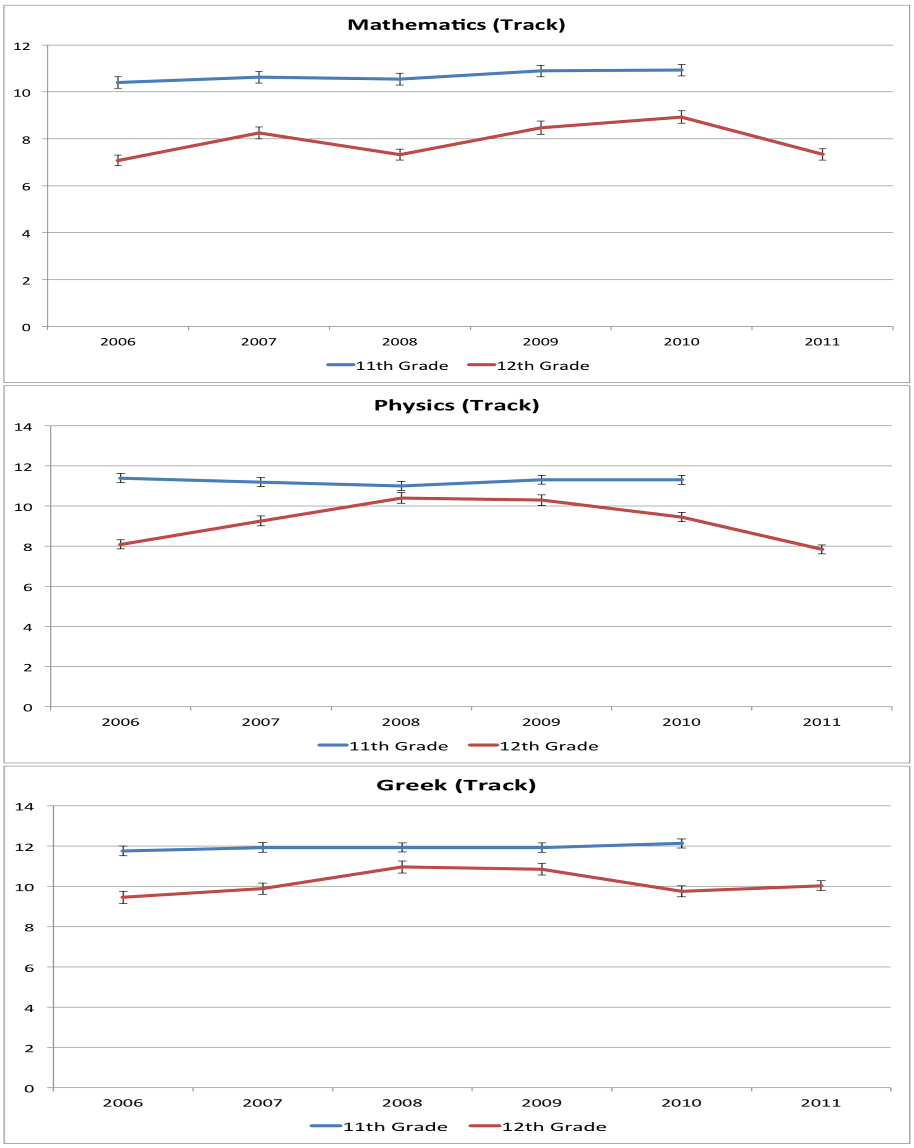

Figure 9: H1N1-infected high school students in Greece

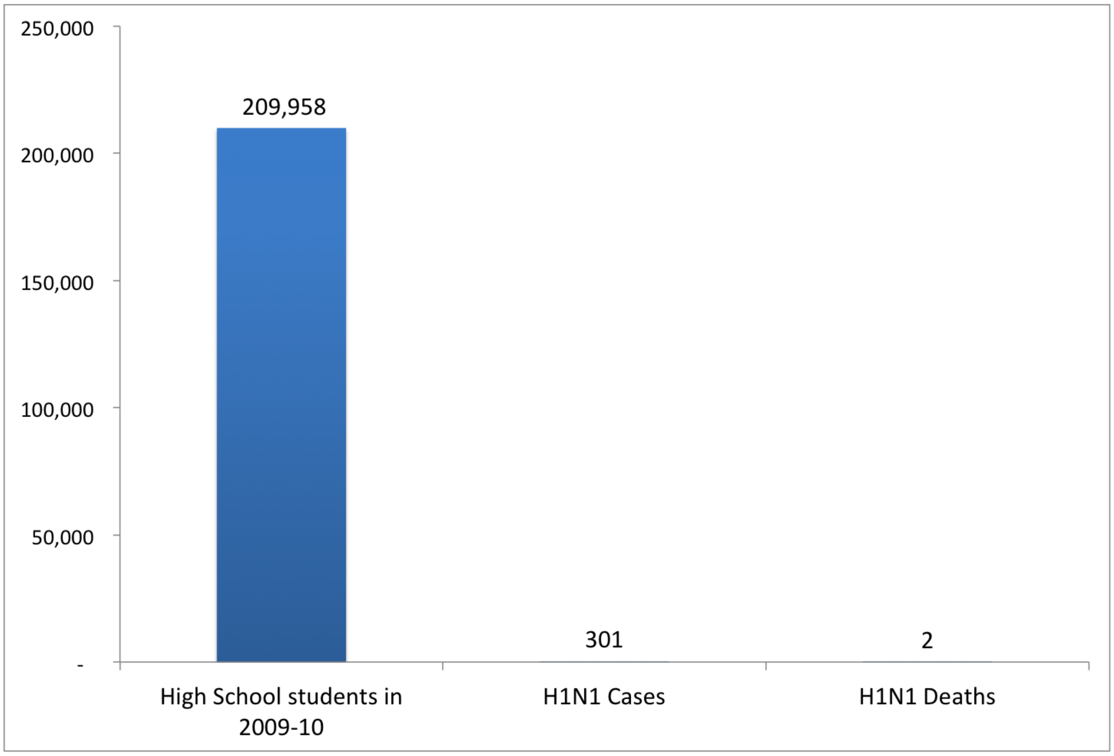

Figure 10: Swine Flu Cases in Greece in 2009-2010

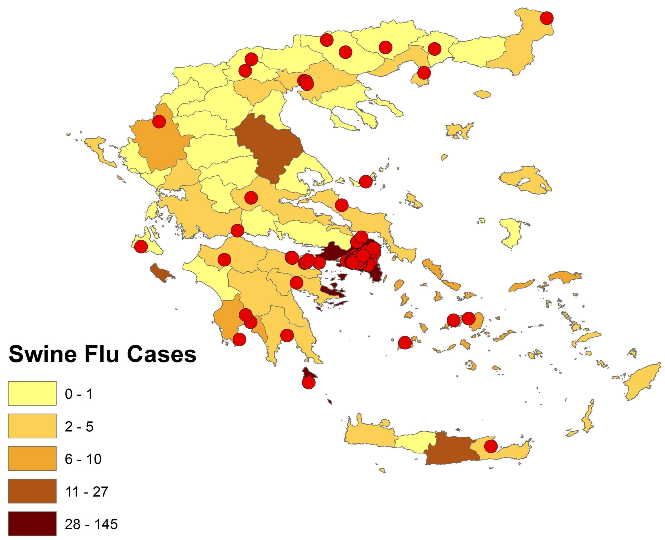

Table 4: Returns to Absences using Attendance Policy Instrument

	GPA			
	(1)	(2)	(3)	(4)
Absences	-0.065	-0.022	-0.020	0.041
	(0.002)***	(0.002)***	(0.002)***	(0.011)***
Instrument	None	None	None	Flu Reform
Grade FE	✓	✓	✓	✓
Class Controls	✓	✓	✓	✓
Lagged Score		✓	✓	✓
School FE			✓	✓

Sample: 58,923 obs (19,641 individuals). Scores are standardized by school and grade. Cluster-robust standard errors at the class level are reported in parentheses. Class controls include average lagged performance, and average lagged absences of class peers. Unit of Absences is tens of hours of classes. All specifications include a constant and student controls. *,**,*** denotes significance at the 10%,5% and 1% level respectively.

Figure 11: Timing of absences in 2009-2010

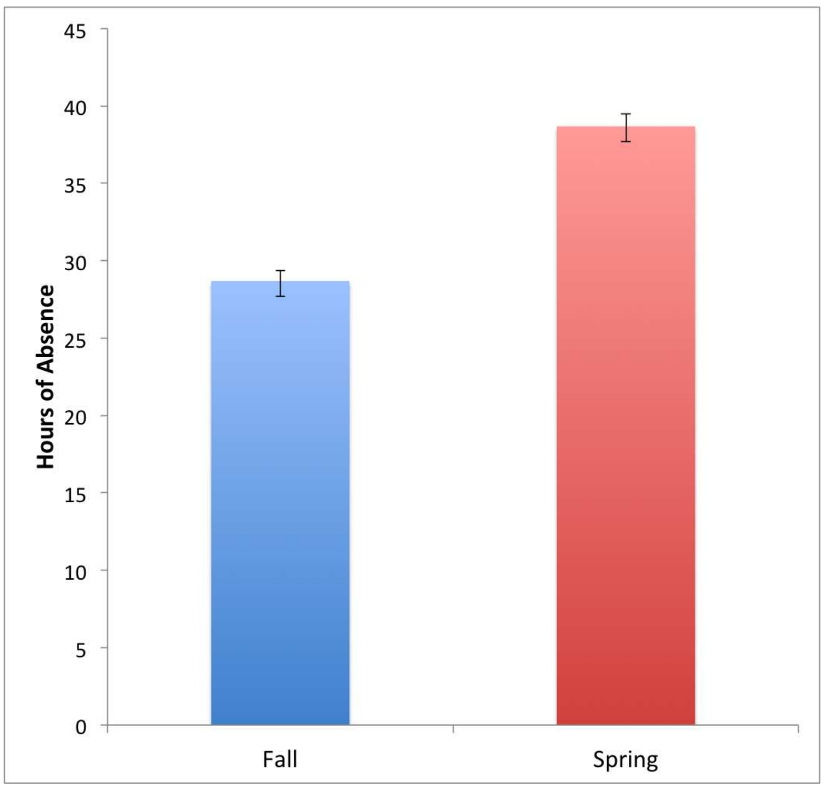

Figure 12: Common Trends Assumption

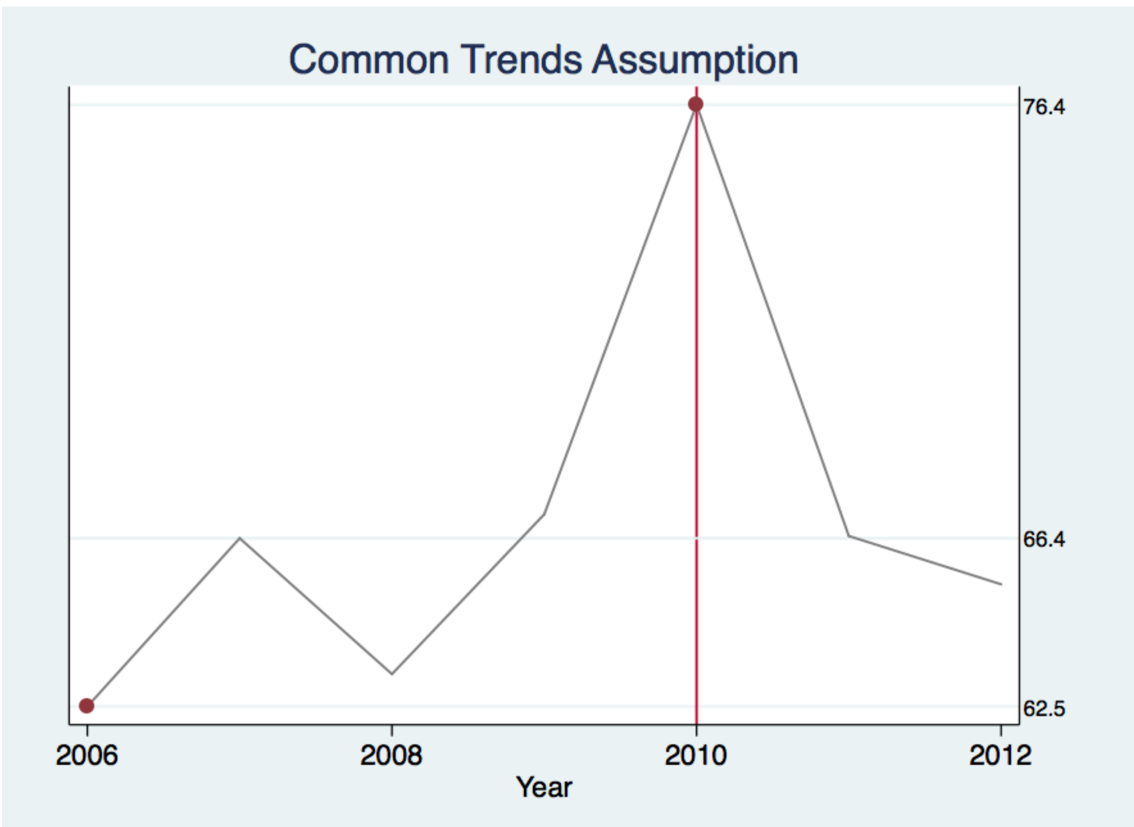

Figure 13: Placebo Test

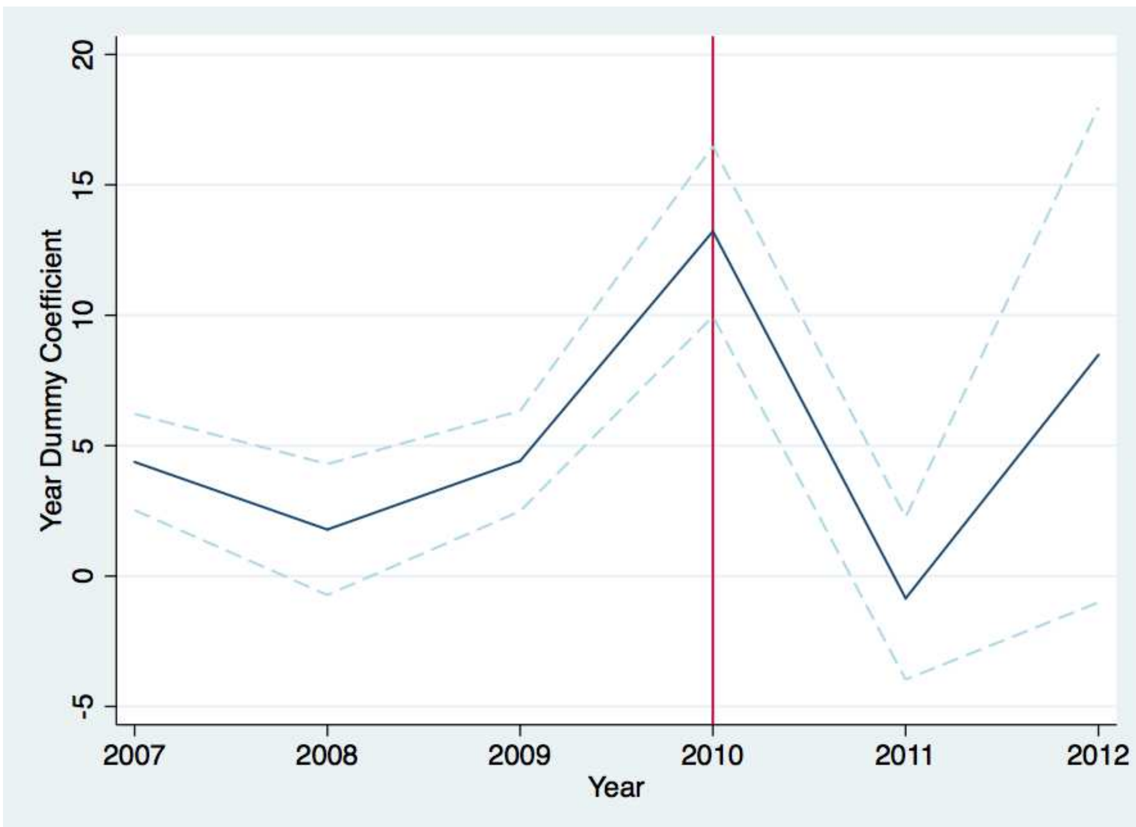

Table 5: Reduced Form, and First Stage Results

	Absences	**GPA**
	First Stage	**Reduced Form**
Flu Shock	1.121	0.046
	(0.067)***	(0.012)***
F-Statistic	277.23	

Note: Sample: 58,923 obs (19,641 individuals). Cluster-robust standard errors at the classroom level are reported in parentheses. Specifications include, student controls lagged score, class controls, grade fixed effects, and school fixed effects. Class controls include average lagged performance, and average lagged absences of class peers. Unit of Absences is tens of hours of classes. *,**,*** denotes significance at the 10%,5% and 1% level respectively.

Table 6: Robustness

	GPA							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Absences	-0.066	-0.069	-0.022	-0.021	-0.020	-0.021	0.026	0.019
	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.011)**	(0.010)*
Instrument	None	None	None	None	None	None	Flu Reform	Flu Reform
Grade FE	✓	✓	✓	✓	✓	✓	✓	✓
Class Controls	✓	✓	✓	✓	✓	✓	✓	✓
Linear Trend	✓	✓	✓	✓	✓	✓	✓	✓
Lagged Score			✓	✓	✓	✓	✓	✓
School FE					✓	✓	✓	✓
School-Specific Linear Trend		✓		✓		✓		✓

Sample: 58,923 obs (19,641 individuals). Scores are standardized by school and grade. Cluster-robust standard errors at the class level are reported in parentheses. Class controls include average lagged performance, and average lagged absences of class peers. Unit of Absences is tens of hours of classes. All specifications include a constant and student controls. *,**,*** denotes significance at the 10%,5% and 1% level respectively.

Table 7: Reduced Form, and First Stage Results

	Absences		GPA	
	First Stage		**Reduced Form**	
Flu Shock	1.222	1.121	0.031	0.023
	(0.077)***	(0.075)***	(0.014)**	(0.012)*
Linear Trend	✓	✓	✓	✓
School-Specific Linear Trend		✓		✓
F-Statistic	254.08	261.25		

Note: Sample: 58,923 obs (19,641 individuals). Cluster-robust standard errors at the individual level are reported in parentheses. Specifications include, student controls lagged score, class controls, grade fixed effects, and school fixed effects. Class controls include average lagged performance, and average lagged absences of class peers. Unit of Absences is tens of hours of classes. *,**,*** denotes significance at the 10%,5% and 1% level respectively.

Table 8: Heterogeneous Propensity to Skip Class: Cognitive Ability

	Total Absences		Excused Absences		Unexcused Absences	
	(1)	(2)	(3)	(4)	(5)	(6)
Flu	1.007	0.992	0.466	0.464	0.571	0.559
	(0.097)***	(0.094)***	(0.073)***	(0.071)***	(0.046)***	(0.046)***
Flu $\times$ ***Cognitive Ability***	0.192	0.194	0.220	0.222	-0.034	-0.033
	(0.150)	(0.149)	(0.115)*	(0.115)*	(0.067)	(0.066)
Cognitive Ability	-2.002	-2.005	-0.411	-0.413	-1.586	-1.587
	(0.055)***	(0.055)***	(0.042)***	(0.042)***	(0.025)***	(0.025)***
School FE	✓	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓	✓
Class Controls	✓	✓	✓	✓	✓	✓
Linear Trend	✓		✓		✓	
School-Specific Linear Trend		✓		✓		✓
R^2	0.32	0.33	0.29	0.30	0.20	0.20

Note: sample: 58,923 obs (19,641 individuals). Cluster-robust standard errors at the classroom level are reported in parentheses. Class controls include average lagged performance, and average lagged absences of class peers. Unit of Absences is tens of hours of classes. All specifications include a constant and student controls for gender, age, and age squared. *,**,*** denotes significance at the 10%,5% and 1% level respectively.

Table 9: Heterogeneous Propensity to Skip Class: Peer Quality

	Total Absences		Excused		Unexcused	
	(1)	(2)	(3)	(4)	(5)	(6)
Flu	5.236	5.429	4.256	4.570	0.705	0.577
	(2.221)**	(2.182)**	(1.625)***	(1.605)***	(1.167)	(1.151)
Flu $\times$ ***Peer Quality***	-1.494	-1.573	-1.342	-1.458	-0.037	0.004
	(0.830)*	(0.816)*	(0.608)**	(0.600)**	(0.434)	(0.428)
Peer Quality	0.204	0.456	0.049	0.258	0.063	0.104
	(0.413)	(0.419)	(0.306)	(0.312)	(0.230)	(0.226)
School FE	✓	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓	✓
Class Controls	✓	✓	✓	✓	✓	✓
Lagged Score	✓	✓	✓	✓	✓	✓
Linear Trend	✓		✓		✓	
School-Specific Linear Trend		✓		✓		✓
R^2	0.26	0.27	0.27	0.28	0.14	0.14

Note: sample: 58,923 obs (19,641 individuals). Cluster-robust standard errors at the classroom level are reported in parentheses. Class controls average lagged absences of class peers. Unit of Absences is tens of hours of classes. All specifications include a constant and student controls for gender, age, and age squared. *,**,*** denotes significance at the 10%,5% and 1% level respectively.

Table 10: Heterogeneous Propensity to Skip Class: Postcode Income

	Total Absences		Excused		Unexcused	
	(1)	(2)	(3)	(4)	(5)	(6)
Flu	10.838	11.013	7.867	8.552	1.708	1.067
	(3.189)***	(3.381)***	(2.682)***	(2.815)***	(1.407)	(1.508)
Flu $\times$ ***Log(Income)***	-0.965	-0.984	-0.724	-0.792	-0.111	-0.048
	(0.320)***	(0.340)***	(0.269)***	(0.283)***	(0.142)	(0.152)
School FE	✓	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓	✓
Class Controls	✓	✓	✓	✓	✓	✓
Lagged Score	✓	✓	✓	✓	✓	✓
Linear Trend	✓		✓		✓	
School-Specific Linear Trend		✓		✓		✓
R^2	0.26	0.27	0.27	0.28	0.14	0.14

Note: sample: 58,923 obs (19,641 individuals). Cluster-robust standard errors at the classroom level are reported in parentheses. Class controls average lagged absences of class peers. Unit of Absences is tens of hours of classes. All specifications include a constant and student controls for gender, age, and age squared. *,**,*** denotes significance at the 10%,5% and 1% level respectively.

Table 11: Heterogeneous Returns to Absences: Cognitive Ability

Dependent Variable: GPA		
	(1)	(2)
Absences	-0.002	-0.002
	(0.016)	(0.015)
Absences $\times$ ***Cognitive Ability***	0.004	0.004
	(0.002)***	(0.002)***
Cognitive Ability	2.154	2.156
	(0.106)***	(0.105)***
School FE	✓	✓
Grade FE	✓	✓
Class Controls	✓	✓
Linear Trend	✓	
School-Specific Linear Trend		✓
$Cragg-Donald\ F\ statistic$	556.717	545.294

Note: sample: 58,923 obs (19,641 individuals). Cluster-robust standard errors at the classroom level are reported in parentheses. Class controls include average lagged performance, and average lagged absences of class peers. Unit of Absences is tens of hours of classes. All specifications include a constant and student controls for gender, age, and age squared. *,**,*** denotes significance at the 10%,5% and 1% level respectively.

Table 12: Heterogeneous Returns to Absences: Peer Quality

Dependent Variable: GPA		
	(1)	(2)
Absences	-0.010	-0.276
	(0.424)	(0.459)
Absences × Peer Quality	0.013	0.110
	(0.159)	(0.172)
Peer Quality	-0.474	-1.275
	(1.149)	(1.234)
School FE	✓	✓
Grade FE	✓	✓
Class Controls	✓	✓
Lagged Score	✓	✓
Linear Trend	✓	
School-Specific Linear Trend		✓
$Cragg - Donald\ F\ statistic$	204.957	170.676

Note: sample: 58,923 obs (19,641 individuals). Cluster-robust standard errors at the classroom level are reported in parentheses. Class controls include average lagged performance, and average lagged absences of class peers. Unit of Absences is tens of hours of classes. All specifications include a constant and student controls for gender, age, and age squared. *,**,*** denotes significance at the 10%,5% and 1% level respectively.

Table 13: Heterogeneous Returns to Absences: Postcode Income

Dependent Variable: GPA		
	(1)	(2)
Absences	0.120	-0.400
	(0.479)	(1.272)
Absences $\times$ ***Log(Income)***	-0.010	0.042
	(0.048)	(0.128)
School FE	✓	✓
Grade FE	✓	✓
Class Controls	✓	✓
Lagged Score	✓	✓
Linear Trend	✓	
School-Specific Linear Trend		✓
$Cragg - Donald\ F\ statistic$	293.669	43.371

Note: sample: 58,923 obs (19,641 individuals). Cluster-robust standard errors at the classroom level are reported in parentheses. Class controls include average lagged performance, and average lagged absences of class peers. Unit of Absences is tens of hours of classes. All specifications include a constant and student controls for gender, age, and age squared. *,**,*** denotes significance at the 10%,5% and 1% level respectively.

Table 14: Heterogeneous Returns to Absences: Subjects

	Greek		**Mathematics**	
	(1)	(2)	(3)	(4)
Absences	-0.033	-0.038	0.026	0.029
	(0.016)**	(0 .016)**	(0.014)*	(0.014)**
First Stage F-Statistic	236.19	256.92	236.58	256.26
Grade FE	✓	✓	✓	✓
Class Controls	✓	✓	✓	✓
Lagged Score	✓	✓	✓	✓
School FE	✓	✓	✓	✓
Linear Trend	✓		✓	
School-Specific Linear Trend		✓		✓

Sample: 58,923 obs (19,641 individuals). Scores are standardized by school, and grade. Cluster-robust standard errors at the class level are reported in parentheses. Class controls include average lagged performance, and average lagged absences of class peers. Unit of Absences is tens of hours of classes. All specifications include a constant and student controls. *,**,*** denotes significance at the 10%,5% and 1% level respectively.

Table 15: Heterogeneous Returns to Absences: Track

	Track Average Score					
	Classics		**IT**		**Science**	
	(1)	(2)	(3)	(4)	(5)	(6)
Absences	-0.012	-0.006	0.039	0.042	0.164	0.164
	(0.012)	(0.013)	(0.015)**	(0.016)**	(0.035)***	(0.035)***
First Stage F-Statistic	168.66	138.89	132.44	114.15	35.48	33.70
Class Controls	✓	✓	✓	✓	✓	✓
Lagged Score	✓	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓	✓
Linear Trend	✓		✓		✓	
School-Specific Linear Trend		✓		✓		✓
# of Students	7,750		8,809		2,384	

Data: Panel for 18,943 individuals. Scores are standardized by school, grade, and track. Cluster-robust standard errors at the class level are reported in parentheses. Class controls include average lagged performance, and average lagged absences of class peers. Unit of Absences is tens of hours of classes. All specifications include a constant and student controls. *,**,*** denotes significance at the 10%,5% and 1% level respectively.

10 Appendix

10.1 Descriptive Statistics of Grade Retention

Table 16: Average Grade Retention

	Mean	s.d.
Retention Rate	0.038	0.191
Grade		
10th	0.058	0.235
11th	0.043	0.202
12th	0.015	0.122
Gender		
Males	0.051	0.221
Females	0.027	0.162
Age		
16 or younger	0.041	0.199
16-17	0.034	0.180
17-18	0.023	0.151
18 or older	0.190	0.393
Reason		
Due to performance	0.025	0.155
Due to absences	0.013	0.114
Class Mean Math Score		
Highest Quintile	0.021	0.143
Fourth Quintile	0.027	0.163
Third Quintile	0.036	0.186
Second Quintile	0.061	0.239
Lowest Quintile	0.068	0.251
Class size		
Highest Quintile	0.039	0.194
Fourth Quintile	0.039	0.194
Third Quintile	0.038	0.190
Second Quintile	0.040	0.196
Lowest Quintile	0.043	0.203
Year		
2006	0.038	0.191
2007	0.042	0.200
2008	0.039	0.195
2009	0.039	0.194
2010	0.041	0.197
2011	0.038	0.193
2012	0.022	0.148

Sample: 106,838 obs; 51,666 individuals.

Table 17: Grade Retention due to absences

	Mean	s.d.
Grade		
10th	0.019	0.135
11th	0.016	0.126
12th	0.006	0.075
Midterm Math Score		
Highest Quintile	0.001	0.029
Fourth Quintile	0.001	0.024
Third Quintile	0.000	0.021
Second Quintile	0.000	0.020
Lowest Quintile	0.031	0.173
Class Mean Math Score		
Highest Quintile	0.009	0.095
Fourth Quintile	0.010	0.102
Third Quintile	0.013	0.112
Second Quintile	0.018	0.133
Lowest Quintile	0.024	0.152
Gender		
Males	0.016	0.126
Females	0.011	0.104
Age		
16 or younger	0.006	0.080
16-17	0.010	0.098
17-18	0.011	0.102
18 or older	0.149	0.356
Class size		
Highest Quintile	0.011	0.102
Fourth Quintile	0.013	0.111
Third Quintile	0.013	0.112
Second Quintile	0.015	0.122
Lowest Quintile	0.017	0.130
Year		
2006	0.013	0.115
2007	0.016	0.124
2008	0.015	0.120
2009	0.015	0.121
2010	0.011	0.107
2011	0.011	0.103
2012	0.006	0.080

Sample: 106,838 obs; 51,666 individuals.