ESSAYS ON EXTERNAL INFLUENCES ON ACADEMIC ACHIEVEMENT: EVIDENCE FROM POLITICAL UNREST AND SEVERE FLOODS IN THAILAND

by

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A dissertation submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics

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ABSTRACT

Since 2006 at least 843 protests have occurred in 87 countries (Ortiz et al. 2013). My first essay examines the impact of political protests on student achievement. The chief conceptual difficulty in identifying the effect of protests on student achievement is their non-random nature. To address this problem, I exploit the political protests in Thailand in 2008 and 2010 as quasi-experiments to measure their effect on the national examination, the O-net, conditional on school fixed effects. The estimates suggest that the protests had a negative and significant effect on all test scores except for the mathematics test scores, perhaps because students were able to study mathematics more easily outside of school. The absolute sizes of the change in test score as a result of the protests range from 0.05 to 0.14 standard deviations, depending on the subject.

Over 300 natural disasters affected more than 140 million people in 2014 (Guha-Sapir, Below, and Hoyois 2016). My second essay examines the impact of severe flooding on student achievement. By using a difference-in-differences strategy, I exploit the severe flooding in Thailand in 2011 as a natural experiment to measure its effect on the national examination, the O-net. The estimates suggest that the flood had a negative and significant effect on all test scores for grade 6, except for social studies. In addition, for grade 9 the flood had a negative and significant effect on all test scores. But, for grade 12 the flood had no significant effect on test scores, except for social studies. The absolute sizes of the change in test score as a result of the flood range from 0.03 to 0.11 standard deviations, depending on the subject and level.

Chapter 1

PROLONGED PROTESTS AND STUDENT ACHIEVEMENT: EVIDENCE FROM POLITICAL UNREST IN THAILAND

1.1 Introduction

Political unrest, often signified by protest, can affect countries in several ways such as economic growth and investment. Alesina et al. (1996) found that in countries and time periods with high political instability, economic growth is significantly lower. Researchers have also found some empirical evidence that political instability can deter investment at the aggregate level (Barro 1991; Pindyck and Solimano 1993; Alesina and Perotti 1996; Julio and Yook 2012). In addition to the impacts on economic growth and on investment, political unrest can also affect health, tourism and education (Sönmez 1998; Neumayer 2004; Østby and Urdal 2011; Halim, Bohara, and Ruan 2010; Dupas and Robinson 2012). Although, at least 843 protests occurred in 87 countries since 2006, little is known about the impact of protest on education (Ortiz et al. 2013). This paper seeks to fill the gap by estimating the impact of prolonged protests on student achievement, using a unique natural experiment in Thailand.

Protests can adversely affect education through several channels. First, protests lead to a loss in instructional days and school closures. Studies have found a positive relationship between instructional days and students' test scores (Marcotte 2007; Marcotte and Hemelt 2008; Hoxby and Murarka 2009; Abdulkadiroğlu et al. 2011; Dobbie and Fryer 2011). Second, in addition to the loss of instructional days, when

schools are still in operation, protests might lead to higher student and teacher absences because both students and teachers may have difficulty in commuting between their homes and schools. Researchers have found that classroom attendance has a positive relationship with student achievement (Devadoss and Foltz 1996; Lamdin 1996; Roby 2004; Gottfried 2009; Gottfried 2010). Clotfelter, Ladd, and Vigdor (2009) found that teacher absences adversely affect student achievement. Third, protests might create an unfavorable environment for schooling. In particular, schools located very close to the protest sites might be affected by noise pollution as a by-product of the protests. Studies have found an association between a noisy environment and reading problems (Bronzaft and McCarthy 1975; Evans and Maxwell 1997; Maxwell and Evans 2000; Haines et al. 2001).

To evaluate the impact of protests on student achievement, I use the political unrest in Bangkok as a quasi-exogenous shock. Between 2008 and 2014, 3 major protests occurred in central Bangkok.[1] These protests led to school closures and educational disruption for some, but not all schools, in Bangkok. In this paper, I focus only on schools in Bangkok and its vicinity because the impact of these protests is localized. My primary outcome of interest is the school level national standardized examination scores, the O-net, as a proxy for student academic achievement. I combine the school-level O-net examination scores from the National Institute of Educational Test Service (NIETS) with school specific data from the Ministry of Education for academic years 2006-2013.

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[1] A third protest occurred in late 2013 and ended in early 2014. Due to data limitations, I limit my attention to the first two rounds of protests that occurred in 2008 and 2010.

The political unrest in Thailand provides me with a unique natural experiment setting. When protests occurred and turned violent, schools near the protest sites were temporarily closed for a few days or weeks, creating the variation in instructional days between schools within Bangkok and vicinity, naturally separating schools into treatment and control groups. In this chapter, I treat schools in Bangkok and vicinity that were unaffected by the protest as the control group. The unique setting from political unrest in Bangkok allows me to estimate the impact of protests on end of year examination scores. My estimates suggest that the protests had a negative and significant effect on all test scores except for mathematics test scores. The impact of the protests on mathematics test scores is positive and significant. The absolute sizes of the change in test score as a result of the protests range from 0.05 to 0.14 standard deviations, depending on the subject. My estimates capture the effect of the protests on end of year examination scores that run not only through the loss of instructional days, but also through other channels such as a potential increase in student absence.

This study makes three contributions to the literature. First, it provides robust empirical evidence that protests had a negative and significant effect on student achievement in all subjects except mathematics. Prior works have investigated the impact of different types of disruption to a school's schedule on student achievement; however, no well-identified research has examined protests as a disruption to a school's schedule. Marcotte (2007), Marcotte and Helmelt (2008), Hansen (2011) and Goodman (2014) provide evidence of the impact of bad weather which disrupts a school's schedule on student achievement. Researchers have also studied the impact of natural disasters, such as earthquakes on student performance. Pietro (2015) examined and found the negative impact of the 2009 L'Aquila earthquake on academic

performance. To fill the gap in the literature, my work provides the first well-identified research on the impact of political protests on student achievement. It also helps government, policy makers, and educators to have a better understanding about the impact of protests on education.

Second, my estimates provide further empirical evidence on the effects of disruption to a school's schedule on academic achievement. My estimates which range from 0.04 to 0.15 standard deviations are consistent with earlier work on the impact of disruptions to a school's schedule on student performance. For instance, Marcotte and Hemelt (2008) found that losing school days due to unscheduled closings has negative effects on performance on state assessments. Hansen (2011) found an additional day with snow greater than 4 inches decreases test scores by .015 standard deviations. My findings further support policymakers that additional support and resources to affected schools might be needed to lessen the adverse impact of the political protests on the test scores in most subjects.

Third, my work is the first empirical research that investigates the impact of the 2008 and 2010 protests in Bangkok on educational outcome. The protests in Bangkok, especially the one in 2010, is one of the global protests that generated the most injuries since 2006 (Ortiz et al. 2013). However, none of the existing literature examines the impact of these protests in Bangkok on student achievement. Thus, my work seeks to fill this gap.

The remainder of this chapter is organized as follows. Section 1.2 reviews the findings of earlier studies investigating the impacts of instructional time, student absence, and interruption to schooling, on academic outcome. Section 1.3 describes the background of the education system and political instabilities in Thailand. Section

1.4 outlines the empirical strategy. Section 1.5 describes the data. Section 1.6 presents the estimated impact of the protests on O-net examination scores. Section 1.7 presents several specification checks. Section 1.8 concludes.

1.2 Literature Review

Prior works that investigated the impact of instructional time on student achievement focused mostly on the amount of time built into the school schedule. Pischke (2007) took advantage of the variation introduced by the West German short school years in 1966-7, which exposed some students to a total of about two thirds of a year less of schooling while enrolled. He found that the length of school year was positively correlated with academic performance. Krashinsky (2014) used a unique policy change, eliminating the fifth year of high school, in Ontario, Canada, which provides direct evidence on how reducing the length of high school would impact student performance in the university. He found that cohorts with four years of high school performed significantly worse than those who attended high school for five years in all subjects, even after the age difference between the cohorts was accounted for. Lavy (2012) examined how student academic achievement was affected by a school finance policy experiment undertaken in elementary schools in Israel. The experiment altered teaching budgets and also the length of the school week. He found that spending more time at school led to an increased academic achievement.

In a cross-country study, Lee and Barro (2001) examined the impacts of many different types of school resources including the length of the school term on internationally comparable test scores. They found that the length of the school term was positively correlated with mathematics and science scores but negatively correlated with reading scores. Wößmann (2003) also analyzed cross-country test

score data. He found that instruction time (in minutes per year) at the relevant grade level of the school was statistically significantly positively related to student performance in mathematics and science. Lavy (2010) estimated the effects of instructional time on academic achievement in math, science and reading. The evidence from a sample of 15 year olds from over fifty countries that participated in PISA 2006 consistently showed that instructional time had a positive and significant effect on test scores. The estimated effect of instructional time in the sample of developing countries was much lower than the size of the effect in developed countries.

Researchers have used the variation in instructional time caused by inclement weather to examine the impact of instructional time on academic performance. Marcotte (2007) identified the impact of schooling on test scores by using the variation in winter weather in Maryland that made non-trivial differences in the number of instructional days students received prior to taking the Maryland School Performance Assessment (MSPAP) exams. He found that students who took exams in years with heavy snowfall performed significantly worse than their peers in the same schools who took exams in other years. Marcotte and Hemelt (2008) found that losing school days to unscheduled closings had negative effects on performance. They also found that school closing had larger effects on performance for students in the lower grades. Hansen (2011) also investigated the impact of instructional days on student achievement. He took advantage of exogenous variation in instructional time due to both weather and state mandated shifts in test administration. Weather-related cancellations and test date shifts both offered statistically significant evidence that additional school days increased student performance.

Goodman (2014) studied the impact of instructional time lost due to absences, as well as to school closures, on achievement using fixed effects and instrumental variable approaches. However, prior works (Marcotte 2007; Marcotte and Hemelt 2008; Hansen 2011) had relied on the assumption that bad weather could serve as an instrument for the number of snow days experienced by a given school or student — allowing identification of the impact of snow days. Goodman showed that bad weather violated the exclusion restriction because bad weather affected not only school closures but also student absences. He found that all of the impact of the bad weather ran through student absences and none through school closures. Thus, he claimed that his paper provided some of the first well-identified evidence on the impact of student absences on achievement. He found that there was a strong relationship between student absences and achievement but there was no relationship between school closures and achievement.

1.3 Background

1.3.1 Education System in Thailand

Thai citizens receive free education up to twelve years according to Thailand's constitution, and all Thai citizens are required to attend at least nine years of schooling (Ministry of Education 2015). Not all schools provide free education. Only public schools that are supported by the government provide free education for their students. Students who choose to attend private schools are required to pay tuition and fees.

Students in Thailand start in primary school (*Pratom Suksa*) and continue on to secondary school (*Mathayom Suksa*). Primary schools have a six-year curriculum — *Pratom Suksa* 1 (P1) to *Pratum Suksa* 6 (P6). Secondary school curriculum is split

into compulsory three years of lower secondary curriculum — *Mathayom Suksa* 1 (M1) to *Mathayom Suksa* 3 (M3), and another non-compulsory three years of upper secondary curriculum — *Mathayom Suksa* 4 (M4) to *Mathayom Suksa* 6 (M6). Since public secondary schools usually offer both lower secondary curriculum and upper secondary curriculum within the same schools, students are most likely to attend the same school from M1 to M6.

The academic year in Thailand runs from the middle of May to early March of the following year with a brief break in October. In early February, M6 students, equivalent to U.S. grade 12, are required to take an O-net examination organized by the National Institute of Educational Test Service (NIETS). The O-net examination consists of 8 subjects: Thai, social studies, science, mathematics, English, physical education, art, and technology. Each subject is graded from 0 to 100 points. Students can take this examination only once. An O-net combined score is one of the requirements for university application. As a result, M6 students take this examination seriously. P6 and M3 students, equivalent to U.S. grade 6 and 9 respectively, are also obligated to take a similar national examination as one of the graduation requirements for graduation from primary or lower secondary school.

1.3.2 Political Instability in Thailand

A coup d'état on September 19, 2006 resulted from the conflicts between Prime Minister Thaksin Shinawatra and his opponents. After this coup, the military was in power for approximately one year. A general election was held in 2007. Since then, three major protests have occurred in Thailand. But as I have mentioned in the introduction section, I limit my attention to the first two rounds of protests due to data limitations. Figure 1.1 shows the timeline of these protests. Two main groups of

protesters are People Alliance for Democracy (PAD) or “Yellow Shirt” and United Front for Democracy against Dictatorship (UDD) or “Red Shirt.” Yellow Shirt protesters are Mr. Thaksin’s opponents, while Red Shirt protesters are Mr. Thaksin’s supporters.

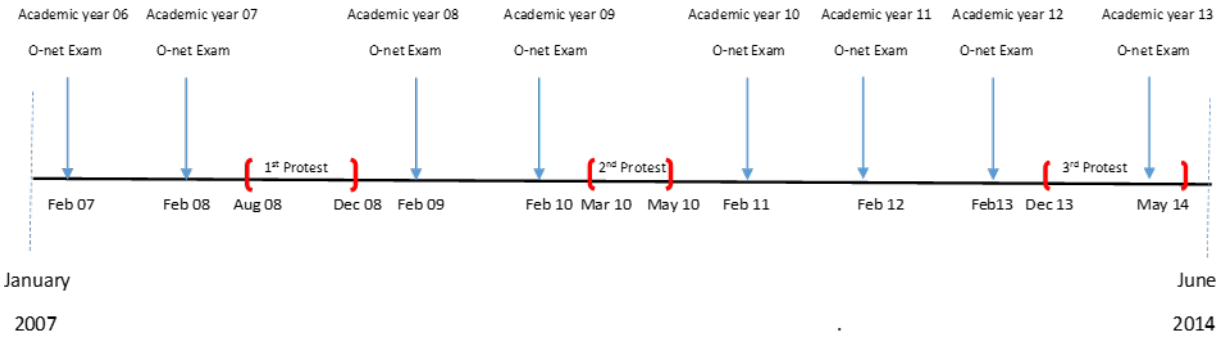

Figure 1.1: Timeline of Events

The People Power Party (PPP), a political party that was supported by Mr. Thaksin, had a landslide victory in the 2007 general election, and set up the coalition government, initiating the Yellow Shirt protestors’ movement. On August 26, 2008, thousands of Yellow Shirt protesters seized Thailand’s Government House. Protesters also attacked other government agencies. The protest turned violent in early October, causing many injuries. In November 2008, Yellow Shirt protesters stepped up the level of the protests by seizing the government’s temporary office at Don Muang Airport and Suvarnabhumi International Airport, the main airport of Bangkok. In December 2008, this first major protest ended because of the verdict of the Constitutional Court that dissolved the PPP party and banned many of PPP members from political activities for five years. Yellow Shirt protesters decided to call off the

protests in all locations. In the empirical strategy, I consider August 2008 to December 2008 as the period of the first protest.

After the dissolution of PPP party, Thailand's new coalition government was run by the Democrat party and their allies. As a result of the verdict of Thailand's Supreme Court, in February 2010, to seize Mr. Thaksin's assets worth approximately $2.3 billion, Red Shirt protesters started the massive protest on March 14, 2010. Thousands of Red Shirt protesters occupied an area not far from the Government House, Phan Fah Bridge. On April 3, 2010, Red Shirt protesters increased the level of the protests by occupying a shopping district in downtown Bangkok, Ratchaprasong. The clashes between the Red shirt protesters and the army started on May 14 and continued until May 19. In the afternoon of May 19, Red Shirt leaders surrendered to the police and asked the protesters to disperse. As a result of this round of major protests, many parts of downtown Bangkok were severely damaged, especially the Ratchaprasong area. In the empirical strategy, I consider March 2010 to May 2010 as the period of the second protest.

1.3.3 Schools during Protests

When protests occurred and the situations remained peaceful, schools operated as usual. However, once the situations turned violent, schools near the protest sites were closed. The government and the Ministry of Education made announcements on national television, radios, and newspapers in order to inform students and parents about the school closures. Each school also made an announcement on the schools' website and Facebook pages. When the situation was not risky but still required caution, the Ministry of Education left it up to the school director whether to close the school on any particular day.

Since O-net examination schedules for P6, M3, and M6 occur in early February each year and are announced earlier in each academic year by the National Institute of Educational Test Service (NIETS), all schools must plan in advance to cover all materials needed for the O-net examination by the end of the academic year. However, protests occurred unexpectedly, and therefore, schools that were affected by the protests were not able to cover all the material needed for the examination due to the loss of instructional days. The variation in the number of instructional days caused by the protests allows me to estimate the causal impacts of the protests on student achievement.

1.4 Empirical Strategy

The chief conceptual difficulty in identifying the effect of protests on student achievement is their typically non-random nature. To address the problem, I exploit the quasi-exogenous change in student achievement conditional on school fixed effects that resulted from the political protests in Thailand in 2008 and 2010.

In order to evaluate the impact of protests on student achievement, I use a difference-in-differences strategy. I begin by defining the treatment group as the schools that were affected by either of the two rounds of the protests, ignoring whether the schools were affected by the first or second round of the protests. I define school *s* as being affected by the protests if the school *s* is within 4 kilometers from the center of any protest location.[2] Then I estimate the impact of the protests as follows:

[2] The 4-kilometer threshold is arbitrarily chosen. As shown in the robustness checks section, using other thresholds to define treated schools yields qualitatively similar results.

$$Score_{st} = \alpha + \beta(EverProtest_s \times ProtestYear_t) + \lambda(EverProtest_s \times Trend_t) + \delta_s + \delta_t + \varepsilon_{st} \quad (1.1)$$

where $Score_{st}$ is the school level O-net examination scores (i.e., overall average scores, subject specific test scores) of school *s* in academic year *t*; $EverProtest_s$ is a dummy variable that takes the value of 1 if the school *s* was affected by either of the two rounds of protests, and 0 otherwise; $ProtestYear_t$ is a dummy variable that takes the value of 1 if academic year *t* is 2008 or 2010; $Trend_t$ is a time trend variable; δ_s are school fixed effects that represent an individual school's unobserved time invariant characteristics; δ_t are academic year fixed effects; ε_{st} is the idiosyncratic error term. Since the first round of protests occurred during August 2008 and December 2008 as shown in Figure 1.1, the impact of the first round of the protests should show up on the O-net examination scores in academic year 2008. Similarly, the second round of protests occurred in 2010, the impact of the second round of the protests should show up on the O-net examination scores in academic year 2010. This is why the dummy variable, $ProtestYear_t$ takes the value of 1 if academic year *t* is 2008 or 2010. In this baseline model, β is the parameter of interest. β captures the impact of having a protest within 4 kilometers from a school in a given year on school's O-net examination scores. If protests adversely affect the O-net examination scores, the test scores of schools that were affected by the protests should be lower than those of the schools that were not affected by the protests.

The standard assumption of the difference-in-differences strategy is that in the absence of the protests, the change in test scores would have not been systematically different across schools in the areas that were affected by the protests and schools in

the areas that were not affected by the protests. Since the parallel trends assumption could be restrictive, I relax the parallel trends assumption by including differential time trends by treatment status in equation (1.1), $Trend_t$. Since the affected schools are located in downtown Bangkok, these affected school tend to have better resources such as better teachers and modern facilities than control schools located outside of Bangkok. As a result, affected schools and control schools can possibly follow a different linear trend. Equation (1.1) presumes that in the absence of protests, the change in test scores of the treated schools deviate from common year fixed effects by following the linear trend captured by λ.

Equation (1.1) is estimated using Ordinary Least Squares (OLS). Since the estimation of equation (1.1) might suffer from potential autocorrelation, ignoring the potential autocorrelation and using the conventional standard errors are likely to yield misleading statistical conclusions. I correct for the potential autocorrelation by clustering the standard errors at the school level. The validity of my analysis also depends on the premise that the assignment of schools to the treatment or control groups is "as if" random, conditional on school fixed effects and protest specific linear trends. However, the protest locations, which in turn determine the assignment of schools to the treatment or the control groups, are not likely to be random. To account for the possible bias, I include the school-specific fixed effects in equation (1.1).

Equation (1.1) treats the two rounds of protests as equivalent. To investigate further whether there is any differences between the impact of the protests in year 2008 and the impact of the protests in year 2010 on the O-net examination scores, I separate the impact of each round of the protests as follows:

$$Score_{st} = \alpha + \beta_1(Protest1_s \times Protest1Year_t) + \beta_2(Protest2_s \times Protest2Year_t) + \lambda_1(Protest1_s \times Trend_t) + \lambda_2(Protest2_s \times Trend_t) + \delta_s + \delta_t + \varepsilon_{st} \quad (1.2)$$

where $Protest1_s$ is a dummy variable that takes the value of 1 if the school *s* was affected by the first round of protests in 2008, and 0 otherwise; $Protest2_s$ is a dummy variable that takes the value of 1 if the school *s* was affected by the second round of protests in 2010, and 0 otherwise; $Protest1Year_t$ is a dummy variable that takes the value of 1 if academic year *t* is 2008, and 0 otherwise; $Protest2Year_t$ is a dummy variable that takes the value of 1 if academic year *t* is 2010, and 0 otherwise; $Trend_t$ is a time trend variable; δ_s are school fixed effects; δ_t are academic year fixed effects; ε_{st} is the idiosyncratic error term. I use the same criterion, 4-kilometer threshold, as in equation (1.1) when determining whether school *s* was affected by the protests. As mentioned earlier that the impact of the first round of the protests should show up on the O-net examination scores in academic year 2008, and the impact of the second round of the protests should show up on the O-net examination scores in academic year 2010, this explains why the dummy variable, $Protest1Year_t$, takes the value of 1 only in academic year 2008, and the dummy variable $Protest2Year_t$ takes the value of 1 if academic year *t* is 2010, and 0 otherwise. In this model, β_1 and β_2 are the parameters of interest. β_1 captures the impact of the 2008 protests on the O-net examination scores of the affected schools. Similarly, β_2 captures the impact of the 2010 protests on the O-net examination of the affected schools. Equation (1.2) allows me to test whether the impacts of these two rounds of protests are statistically different. Since the 2008 protests occurred unexpectedly and the timing of the 2008

protests was closer to the O-net examination date than the ones in 2010, the size of the impact of the 2008 protests might potentially be larger than the ones in 2010. As in equation (1.1), I estimate equation (1.2) using Ordinary Least Squares (OLS) and correct for the potential autocorrelation by clustering the standard errors at the school level. I also include the school-specific fixed effects in equation (1.2).

As in equation (1.1), I include the protest specific linear trends in equation (1.2). Equation (1.2) presumes that in the absence of protest, the change in test scores of the schools that are affected by the 2008 protests and the change in test scores of the schools that are affected by the 2010 protests deviate from common year fixed effects by following the linear trend captured by λ_1 and λ_2 respectively. The specifications as in equation (1.1) and (1.2) — difference-in-differences strategy with time trends, are equivalent to an interrupted time series (ITS) approach that is commonly used in education research (Bloom 2003).

Even though in equation (1.1) and (1.2), I include school-specific fixed effects to control for unobserved time-invariant characteristics of the schools, the challenge relevant to my estimation is to account for omitted variables that are time-varying. To account for the potential selection bias, I estimate additional specifications that include additional time-varying school-specific covariates in the robustness checks section.

1.5 Data

My dataset is generated by combining two primary data sources— the school-level O-net examination scores from academic year 2006 to academic year 2013, and school specific data. The school-level O-net examination scores are from the National Institute of Educational Test Service (NIETS). The data contain the average O-net scores of each primary and secondary school in Thailand of all subjects from academic

year 2006 to academic year 2013. I combine the O-net scores data with the school specific data from the Ministry of Education that contain the number of students enrolled, student teacher ratio, number of teachers, and number of students by gender and by grade for academic years 2006-2013.

In my analysis, I restrict my sample to the schools that are located in Bangkok and nearby vicinities — Nonthaburi, Pathum Thani and Samut Prakan provinces.[3] Schools in Bangkok and nearby vicinities are different from schools in other provinces. Schools in Bangkok and nearby vicinities tend to have better resources such as better teachers and modern facilities. Moreover, students who attend school in Bangkok and nearby vicinities have better access to learning opportunities like better bookstores and abundant tutoring schools. Since I want schools in both treatment and control groups to be similar, only schools located in Bangkok and nearby vicinities are considered in this study. In addition, I exclude vocational schools and international and other special education schools from my sample because these schools do not follow the standard curriculum. The O-net examination is optional for students in these schools.

Moreover, I limit my attention to the test score data of grade 12 students because of the completeness of the data. Grade 12 data contain all 8 academic years, from 2006 to 2013, while grade 6 and grade 9 data set contain only the last 7 and 6 academic years, respectively. The grade 12 data set provides more information of the pre-intervention period than the grade 6 and grade 9 data sets. Since the specification in equation (1.2) relies on measuring the trends prior to the first intervention, it

[3] I define nearby vicinity as provinces that share the same telephone area code as Bangkok.

requires a sample that provides at least two time periods prior to the intervention in 2008. Since the first round of protests occurred during academic year 2008, the grade 12 data set provides two academic years of test score data prior to the first intervention.

Even though the O-net examination consists of 8 subjects, in this study, I limit my attention to only 5 core subjects (Thai, social studies, science, mathematics, and English) for two reasons. First, an O-net combined score, which is one of the requirements for university application, is calculated based on these 5 core subjects. As a result, grade 12 students take these core subject examinations seriously. Therefore, the scores of these core subjects should be more reliable measures of student achievement than including all test scores. Second, NIETS started administering the physical education, art, and occupational & technology examinations in academic year 2007, leaving only one time period available for the pre-intervention data of these three subjects. Therefore, I fit equation (1.1) and (1.2) with the test score data from these 5 core subjects and report the findings in the results section. In addition to the 5 core subjects, I also estimate equation (1.1) and (1.2) using overall average scores and core average scores as additional dependent variables. [4,5]

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[4] To get the overall average score of school *s* in year *t*, I divide the sum of all test scores by the number of exams that are administered in year t. In academic year 2006, only Thai, social studies, mathematics, English and science examinations are administered. Therefore, the overall average score in year 2006 is the average of these 5 subjects. But in all other years, the overall average score is the average of the test scores of all 8 subjects.

[5] The core subjects include Thai, social studies, science, mathematics, and English. Thus, the core average score is the average of the test scores of these core subjects.

Table 1.1: Descriptive Statistics

	Ever Experienced Protest	
	Treated Schools	Control Schools
O-net Examination Scores		
Overall Average Score	42.29	38.39
	(7.55)	(5.27)
Core Average Score	39.41	34.34
	(9.14)	(6.16)
Thai	53.42	48.30
	(9.84)	(7.47)
Social Studies	40.59	37.18
	(7.65)	(5.85)
Mathematics	32.51	25.99
	(12.37)	(9.03)
English	35.04	28.31
	(12.78)	(9.40)
Science	35.47	31.91
	(7.48)	(4.96)
School Data		
Student Enrollment	4272.83	3121.79
	(4190)	(3123)
Number of Teachers	1328.10	985.00
	(1510)	(1163)
Total Number of Schools	614	1684

Note: The total number of schools shown is the number of schools that I have O-net examination score data.

Table 1.1 presents some sample descriptive statistics. In Table 1.1, the treated schools are defined as in equation (1.1). As shown in Table 1.1, the treated schools clearly outperform the control schools in all subjects. It is worth noting that the superior performance of the treated schools does not necessarily invalidate the empirical strategy since the difference-in-differences strategy relies on the change in test score rather than the level of the test score itself. The identification strategy does

not require the average O-net test scores of the treated schools to be similar to those of the control schools.

1.6 Results

Table 1.2 presents the estimates of equation (1.1). Columns 1-7 contain the estimates when the dependent variables are overall average scores, core average scores, and subject specific test scores, respectively. Standard errors clustered at the school level appear in parentheses. All regressions indicate statistically significant effects of protests on test scores except for core average scores. The protests had a negative and significant effect on overall average scores, and the test scores for Thai, social studies, English, and science. However, the impact of the protests on mathematics test scores is positive and significant. Columns 1-7 include the school-specific fixed effects, controlling for the unobserved time-invariant school characteristics, and the year fixed effects, controlling for the possibility that the level of difficulty of the O-net examination might be different across the years.

Table 1.2: Effect on O-net Examination Scores, Equation (1.1)

	Dependent Variable						
	Overall Average Score (1)	Core Average Score (2)	Thai (3)	Social Studies (4)	Math (5)	English (6)	Science (7)
EverProtest× ProtestYear	-0.752***	-0.229	-0.401*	-0.660***	0.946***	-0.746***	-0.285*
	(0.165)	(0.142)	(0.210)	(0.165)	(0.229)	(0.224)	(0.167)
Regression statistics:							
Observations	2298	2298	2298	2298	2298	2298	2298
Adjusted R-square	0.594	0.712	0.575	0.840	0.896	0.740	0.606

Notes: All regressions include school and year fixed effects. Values of robust standard errors clustered at school level appear in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

The point estimate in column 1 indicates that attending a school near the protests causes a 0.752 point drop in the overall average scores, equivalent to a 0.12 standard deviation decline in overall average scores. Column 2 shows that the impact of the protests on the core average scores is not statistically significant. The estimate in column 3 implies that being affected by the protests is associated with 0.4 points or a 0.05 standard deviation decline in Thai test scores. In column 4, the estimate suggests that the protests lower social studies scores by 0.66 points or 0.10 standard deviations.

However, the point estimates in column 5 show that attending a school nearby the protests is associated with 0.946 points or a 0.09 standard deviation increase in the mathematics test scores. A potential explanation might be that students can study mathematics more easily than other subjects while they are outside of school. Moreover, the university central admission system in Thailand requires grade 12 students to take the General Aptitude Test (GAT) and the Professional Academic Aptitude Test (PAT) examinations. These examinations are administered after the O-net examination. When grade 12 students apply to university in Thailand through the central admission process, they have to submit their O-net examination results along with their GAT and PAT test scores. Unlike the O-net examination, the GAT and PAT examinations are optional. Students tend to take only the subjects that are required for their potential course of study. For example, if students are interested in engineering, they are required to take the PAT-Math and PAT-Engineer tests. PAT-Math is required in most of the cases and the weight of PAT-Math alone can be as high as 20% of the total admission score. Therefore, when schools are closed because of the

protests, grade 12 students have higher incentives to work on mathematics rather than languages or social studies.

As I have mentioned in section 1.4, equation (1.1) assumes that there is no difference whether the protest occurred in 2008 or in 2010. Since the 2008 protests occurred unexpectedly and closer to the O-net examination date than the ones in 2010, students in academic year 2008 had less preparation time for the O-net examination than students in academic year 2010. Thus, the magnitudes of the impact of the protests in 2008 should be larger than those of the protests in 2010. Additionally, when the protests occurred in 2010, students and teachers already experienced prior protests. Therefore, students and teachers should be able to adjust to this disruption more easily than when they experienced it in in 2008.

To investigate further, I fit equation (1.2) and perform an F-test to test for differences between the impact of the protests in year 2008 and the impact of the protests in year 2010 on the O-net examination scores. Table 1.3 presents the estimates of equation (1.2). Columns 1-7 contain the estimates when the dependent variables are overall average scores, core average scores and subject specific test scores, respectively. Standard errors clustered at the school level appear in parentheses. As in Table 1.2, columns 1-7 of Table 1.3 include the school-specific fixed effects, and the year fixed effects.

Table 1.3: Effect on O-net Examination Scores, Equation (1.2)

	Dependent Variable						
	Overall Average Score (1)	Core Average Score (2)	Thai (3)	Social Studies (4)	Math (5)	English (6)	Science (7)
Protest1×Protest1Year	-0.845***	-0.192	0.147	-0.665***	1.480***	-1.554***	-0.366
	(0.245)	(0.212)	(0.294)	(0.238)	(0.372)	(0.373)	(0.238)
Protest2×Protest2Year	-0.670***	-0.408**	-1.116***	-0.736***	0.222	-0.0332	-0.375**
	(0.157)	(0.161)	(0.269)	(0.197)	(0.254)	(0.294)	(0.179)
Regression statistics:							
Observations	2298	2298	2298	2298	2298	2298	2298
Adjusted R-square	0.595	0.713	0.576	0.840	0.896	0.741	0.607
F-test of *(Protest1×Protest1Year = Protest2×Protest2Year)*	0.54	0.76	13.30	0.07	9.00	10.15	0.00
p-value of F-test	0.46	0.38	0.00	0.79	0.00	0.00	0.97

Notes: All regressions include school and year fixed effects. Values of robust standard errors clustered at school level appear in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

All regressions in Table 1.3 indicate statistically significant findings. The protests in 2008 had a negative and significant effect on overall average scores, and the test scores for social studies, and English, while the impact of 2008 protests on mathematics test scores is positive and significant. The protests in 2010 had a negative and significant effect on overall average scores, core average scores, and all subject specific test scores except mathematics, and English.

The estimates in column 1 indicate that the protests in 2008 and 2010 are associated with the decline in overall average scores by 0.845 points or 0.14 standard deviations, and 0.670 points or 0.11 standard deviations, respectively. The F-test in column 1 suggests that the equality of the coefficients on the two protests cannot be rejected. The estimates in column 2 imply that the protests in 2011 lower the core average scores by 0.408 points or 0.05 standard deviations. According to the F-test in column 2, the equality of the coefficients on the two protests cannot be rejected.

However, in column 3, the equality of the coefficients on the two protests can be rejected. The estimates in column 3 show that attending a school nearby the protests in 2010 is associated with 1.116 points or a 0.13 standard deviations decline in Thai test scores. In column 4, the results show that the protests in 2008 and in 2010 lower social studies test scores by 0.665 points or 0.10 standard deviations, and by 0.736 points or 0.11 standard deviations, respectively. Unlike column 3, the F-test in column 4 shows that the equality of the coefficients on the two protests cannot be rejected.

According to estimates in column 5, attending a school nearby the protests in 2008 improves mathematics test scores by 1.48 points or 0.14 standard deviations. In contrast, the estimates in column 6 indicate that attending a school nearby the protests

in 2008 lowers English test scores by 1.554 points or 0.144 standard deviations. Based on the results of F-test in columns 5 and 6, the equality of the coefficients on the two protests can be rejected. Even though the improvement in mathematics test scores because of the 2008 protests is contrary to expectation, it is still possible as mentioned earlier. For science, the estimates in column 7 show that the protests in 2011 are associated with a decline in science test scores by 0.375 points, equivalent to a 0.06 standard deviation decline in science test scores, and the equality of the coefficients on the two protests cannot be rejected.

Significant declines in test scores resulting from the protests are not surprising. Moreover, my results which imply that the size of the impact of the 2008 protests is larger than the one in 2010 is not surprising. As I have mentioned earlier, the 2008 protests occurred unexpectedly and closer to the O-net examination date than the ones in 2010. Therefore, in academic year 2008, students had an incentive to spend more time, even when schools were closed, on mathematics which is more important for their university admission. This potentially explains the significant increase in mathematics test score due to the 2008 protests, and the significant drops in overall average scores, social studies test scores, and English due to the 2008 protests. But when the protests in 2010 occurred, students and teachers already had experience. Thus, the adverse impact of the protests is smaller in magnitude but still significant. And the 2010 protests occurred at the very beginning of the academic year, students might find that they had plenty of preparation time for the O-net examination. Therefore, students had no incentive to substitute their time towards mathematics. This might explain why there is no significant increase in mathematics test score due to the 2010 protests.

1.7 Robustness Checks

Table 1.4 presents several specification checks using variants of equation (1.1). To account for potential selection bias, column 2 includes the student-teacher ratio to control for time-varying school-specific factors that are not captured by the inclusion of school fixed effects. In all cases, the results are robust to the inclusion of the student-teacher ratio as an additional explanatory variable. This implies that selection bias is not likely to be a concern in my analysis. Column 3 limits schools in the samples to only the ones located in Bangkok, excluding schools located in nearby vicinity provinces. In all cases, I find that my baseline results are robust.

Columns 4 and 5 of Table 5 are to check the sensitivity of the estimates to the choice of distance from the center of protest sites, which determines treated schools. In my baseline model, I define school *s* as being affected by the protests if the school *s* is located within 4 kilometers from the center of any protest locations. Columns 4 and 5 report the estimates of equation (1) by using 3 kilometers and 5 kilometers, respectively, as the thresholds when determining the treatment group. Results are quite robust. Columns 4 and 5 show that the results in the case of overall average scores, core average scores, social studies, mathematics, and English test scores are robust to the choice of distance used as a threshold to determine treated schools.

Table 1.4: Specification Check, Equation (1.1)

	Baseline (Table 1.2)	Include student/teacher ratio	Exclude vicinities	Distance from center of the protests	
				3 km	5km
	(1)	(2)	(3)	(4)	(5)
Dependent variable: Overall Average Score					
EverProtest× ProtestYear	-0.752***	-0.767***	-0.760***	-0.698***	-0.505***
	(0.165)	(0.166)	(0.185)	(0.183)	(0.166)
Observations	2298	2230	1593	2298	2298
Adjusted R-square	0.594	0.598	0.574	0.592	0.593
Dependent variable: Core Average Score					
EverProtest× ProtestYear	-0.229	-0.260*	-0.277	-0.140	-0.0847
	(0.142)	(0.143)	(0.168)	(0.152)	(0.146)
Observations	2298	2230	1593	2298	2298
Adjusted R-square	0.712	0.720	0.707	0.711	0.712
Dependent variable: Thai					
EverProtest× ProtestYear	-0.401*	-0.443**	-0.405*	-0.247*	-0.192
	(0.210)	(0.209)	(0.242)	(0.223)	(0.216)
Observations	2298	2230	1593	2298	2298
Adjusted R-square	0.575	0.589	0.592	0.573	0.575
Dependent variable: Social Studies					
EverProtest× ProtestYear	-0.660***	-0.705***	-0.723***	-0.656***	-0.398**
	(0.165)	(0.165)	(0.191)	(0.182)	(0.169)
Observations	2298	2230	1593	2298	2298
Adjusted R-square	0.840	0.843	0.820	0.839	0.839
Dependent variable: Mathematics					
EverProtest× ProtestYear	0.946***	0.881***	0.779***	1.072***	0.859***
	(0.229)	(0.230)	(0.249)	(0.248)	(0.223)
Observations	2298	2230	1593	2298	2298
Adjusted R-square	0.896	0.900	0.890	0.896	0.896

Table 1.4 continued

	Baseline (Table 1.2)	Include student/teacher ratio	Exclude vicinities	Distance from center of the protests	
				3 km	5km
	(1)	(2)	(3)	(4)	(5)
Dependent variable: English					
EverProtest× ProtestYear	-0.746***	-0.709***	-0.714**	-0.762***	-0.563***
	(0.224)	(0.227)	(0.288)	(0.232)	(0.239)
Observations	2298	2230	1593	2298	2298
Adjusted R-square	0.740	0.746	0.720	0.740	0.740
Dependent variable: Science					
EverProtest× ProtestYear	-0.285*	-0.321*	-0.319*	-0.107	-0.130
	(0.167)	(0.168)	(0.185)	(0.174)	(0.164)
Observations	2298	2230	1593	2298	2298
Adjusted R-square	0.606	0.619	0.613	0.602	0.603

Notes: All regressions include school and year fixed effects. Values of robust standard errors clustered at school level appear in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Table 1.5 reports several specification checks using variants of (1.2). Similar to Table 1.4, column 2 includes the student-teacher ratio as an additional explanatory variable to control for time-varying school-specific factors. In all cases, the results are robust to the inclusion of the student-teacher ratio. This also implies that selection bias is not likely to be a concern in my analysis. Column 3 limits schools in the samples to only the ones located in Bangkok. By excluding schools located in vicinity provinces, I find that my baseline results are robust.

Columns 4 and 5 of Table 1.5 report the estimates of equation (1.2) using 3 kilometers and 5 kilometers, respectively, as the thresholds to determine treated schools. Results are quite robust. Columns 4 and 5 show that the estimates of the 2008 protests in all cases except for social studies are robust to the choice of distance. Moreover, columns 4 and 5 show that the estimates of the 2010 protests in all cases except for core average scores and science are robust to the choice of distance. The potential explanation why in some cases the estimates lose statistical significance, or change in magnitude, could be that 3 kilometers as the threshold might be too small to include all schools that were affected by the protests. Similarly, 5 kilometers as the threshold might be too large; thus, the treatment group might include schools that were not actually affected by the protests.

Table 1.5: Specification Check, Equation (1.2)

	Baseline (Table 1.3)	Include student/teacher ratio	Exclude vicinities	Distance from center of the protests	
				3 km	5km
	(1)	(2)	(3)	(4)	(5)
Dependent variable: Overall Average Score					
Protest1×Protest1Year	-0.845***	-0.841***	-0.840***	-0.664**	-0.599**
	(0.245)	(0.245)	(0.260)	(0.278)	(0.241)
Protest2×Protest2Year	-0.670***	-0.697***	-0.645***	-0.600***	-0.502***
	(0.157)	(0.158)	(0.178)	(0.172)	(0.161)
Observations	2298	2230	1593	2298	2298
Adjusted R-square	0.595	0.598	0.574	0.592	0.593
F-test of Protest1×Protest1Year = Protest2×Protest2Year	0.54	0.36	0.56	0.06	0.20
p-value of F-test	0.46	0.55	0.46	0.81	0.66
Dependent variable: Core Average Score					
Protest1×Protest1Year	-0.192	-0.212	-0.301	-0.0708	0.0801
	(0.212)	(0.213)	(0.229)	(0.241)	(0.217)
Protest2×Protest2Year	-0.408**	-0.444***	-0.393**	-0.300*	-0.243
	(0.161)	(0.164)	(0.191)	(0.175)	(0.168)
Observations	2298	2230	1593	2298	2298
Adjusted R-square	0.713	0.720	0.707	0.712	0.712
F-test of Protest1×Protest1Year= Protest2×Protest2Year	0.76	0.86	0.11	0.66	1.82
p-value of F-test	0.38	0.35	0.74	0.42	0.17

Table 1.5 continued

	Baseline (Table 1.3) (1)	Include student/teacher ratio (2)	Exclude vicinities (3)	Distance from center of the protests 3 km (4)	Distance from center of the protests 5km (5)
Dependent variable: Thai					
Protest1×Protest1Year	0.147	0.114	0.000950	0.342	0.431
	(0.294)	(0.294)	(0.318)	(0.331)	(0.297)
Protest2×Protest2Year	-1.116***	-1.167***	-1.017***	-0.987***	-0.832***
	(0.269)	(0.269)	(0.308)	(0.283)	(0.275)
Observations	2298	2230	1593	2298	2298
Adjusted R-square	0.576	0.591	0.593	0.574	0.576
F-test of Protest1×Protest1Year= Protest2×Protest2Year	13.30	13.52	6.93	11.54	13.30
p-value of F-test	0.00	0.00	0.01	0.00	0.00
Dependent variable: Social Studies					
Protest1×Protest1Year	-0.665***	-0.666***	-0.803***	-0.450	-0.321
	(0.238)	(0.239)	(0.255)	(0.280)	(0.228)
Protest2×Protest2Year	-0.736***	-0.815***	-0.682***	-0.792***	-0.488**
	(0.197)	(0.195)	(0.223)	(0.212)	(0.205)
Observations	2298	2230	1593	2298	2298
Adjusted R-square	0.840	0.843	0.820	0.839	0.839
F-test of Protest1×Protest1Year= Protest2×Protest2Year	0.07	0.31	0.17	1.17	0.46
p-value of F-test	0.79	0.58	0.68	0.28	0.50
Dependent variable: Mathematics					
Protest1×Protest1Year	1.480***	1.389***	1.042***	1.275***	1.424***
	(0.372)	(0.371)	(0.396)	(0.409)	(0.388)
Protest2×Protest2Year	0.222	0.184	0.261	0.381	0.281
	(0.254)	(0.254)	(0.270)	(0.279)	(0.243)
Observations	2298	2230	1593	2298	2298
Adjusted R-square	0.896	0.900	0.889	0.896	0.897
F-test of Protest1×Protest1Year= Protest2×Protest2Year	9.00	8.27	2.99	3.98	7.21
p-value of F-test	0.00	0.00	0.08	0.04	0.01

Table 1.5 continued

	Baseline (Table 1.3)	Include student/teacher ratio	Exclude vicinities	Distance from center of the protests	
				3 km	5km
	(1)	(2)	(3)	(4)	(5)
Dependent variable: English					
Protest1×Protest1Year	-1.554***	-1.512***	-1.399***	-1.288***	-1.261***
	(0.373)	(0.375)	(0.399)	(0.415)	(0.363)
Protest2×Protest2Year	-0.0332	0.000558	-0.0629	0.0926	0.0348
	(0.294)	(0.295)	(0.378)	(0.312)	(0.293)
Observations	2298	2230	1593	2298	2298
Adjusted R-square	0.741	0.747	0.720	0.741	0.741
F-test of Protest1×Protest1Year= Protest2×Protest2Year	10.15	10.02	6.31	6.89	8.28
p-value of F-test	0.00	0.00	0.01	0.01	0.00
Dependent variable: Science					
Protest1×Protest1Year	-0.366	-0.385	-0.348	-0.233	0.127
	(0.238)	(0.239)	(0.255)	(0.285)	(0.228)
Protest2×Protest2Year	-0.375**	-0.423**	-0.466**	-0.196	-0.209
	(0.179)	(0.182)	(0.196)	(0.192)	(0.187)
Observations	2298	2230	1593	2298	2298
Adjusted R-square	0.607	0.620	0.615	0.604	0.605
F-test of Protest1×Protest1Year= Protest2×Protest2Year	0.00	0.02	0.15	0.01	1.66
p-value of F-test	0.97	0.89	0.70	0.90	0.38

Notes: All regressions include school and year fixed effects. Values of robust standard errors clustered at school level appear in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Another potential threat to the causal inference is an endogenous student mobility, which might occur if protests in 2008 and 2010 caused students to switch from schools in the protest areas to schools in other areas. Tables 1.6 and 1.7 examine the potential threat due to an endogenous student mobility. I replace the dependent variable of equation (1.1) and (1.2) by the number of test takers in each subject. If protests in 2008 and 2010 caused students to switch from schools in the protest areas to schools in other areas, the estimates of the impact of the protests in 2008 and 2010 on the number of test takers in each subject should be statistically significant. However, the estimates from all regressions in Table 1.6 and 1.7 are statistically insignificant. Thus, there is no statistically significant evidence that the protests in 2008 and in 2010 led to a change in number of test takers in any subjects. This implies that endogenous student mobility is not likely to be a concern in my analysis.

Table 1.6: Effect on Number of Test Takers, Equation (1.1)

	Dependent variable: Number of Test Takers				
	Thai	Social Studies	Math	English	Science
	(1)	(2)	(3)	(4)	(5)
EverProtest×ProtestYear	-2.297	-3.168	-2.823	-2.588	-1.909
	(2.818)	(2.728)	(2.767)	(2.814)	(2.839)
Regression statistics:					
Observations	2298	2298	2298	2298	2298
Adjusted R-square	0.287	0.286	0.286	0.286	0.290

Notes: All regressions include school and year fixed effects. Values of robust standard errors clustered at school level appear in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Table 1.7: Effect on Number of Test Takers, Equation (1.2)

	Dependent variable: Number of Test Takers				
	Thai	Social Studies	Math	English	Science
	(1)	(2)	(3)	(4)	(5)
Protest1×Protest1Year	-3.977	-4.789	-4.369	-4.404	-4.274
	(3.937)	(3.921)	(3.923)	(3.908)	(3.940)
Protest2×Protest2Year	1.367	-0.739	0.220	0.777	2.194
	(2.912)	(2.814)	(2.890)	(2.893)	(2.950)
Regression statistics:					
Observations	2298	2298	2298	2298	2298
Adjusted R-square	0.300	0.299	0.299	0.298	0.302

Notes: All regressions include school and year fixed effects. Values of robust standard errors clustered at school level appear in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

1.8 Conclusion

The increased frequency of political unrest around the world in the past decade raises a concern of the impact of political protests on student achievement. However, little is known about the impact of political protests on academic performance. This chapter takes advantage of the political protests in Bangkok in 2008 and 2010 to estimate the impact of the political protests in Thailand on O-net examination test scores. Employing a difference-in-differences strategy, I find a negative and significant impact of the political unrest in Thailand on O-net test scores in all subjects except for mathematics. Specifically, I find that being affected by the protests is associated with a decline in test scores in all subjects except for mathematics by the absolute sizes that range from 0.05 to 0.14 standard deviations. My estimates are

consistent with earlier work on the impact of disruptions to school schedule on student performance. For instance, Marcotte and Hemelt (2008) found that losing school days to unscheduled closings has negative effects on performance on state assessments. Hansen (2011) found an additional day with snow greater than 4 inches decreases test scores by .015 standard deviations.

However, I find a positive and significant impact of the 2008 protests on mathematics test scores. My estimate implies that being affected by the protests is associated with a 0.14 standard deviation increase in the mathematics test scores. The nature of the subject that allows students to practice on their own while they are away from school might be a potential explanation of why the protests have a positive impact on mathematics test scores. Moreover, when schools were closed because of the protests, students could possibly choose to work on the subject that they find more important according to the university admission system. According to Thailand's university admission system, most majors put a significant weight on mathematics subject.

My findings suggest to policymakers that additional support and resources to affected schools might be needed to lessen the adverse impact of the political unrest on the test scores in most subjects. One potential recommendation is to adopt technology when protests interrupt a school's schedule. Online classroom or online assignments can be used to lower the adverse impact of the protests. However, policy makers should be aware that when protests occur close to the national examination schedule as in 2008, students might have more incentive to spend more time on mathematics and perhaps because students were able to study mathematics more easily outside of school. Therefore, to use online assignments as a tool to lower the adverse

impact of the protests, educators and policy makers should assign the assignments from all subjects to ensure that students will be able to catch up on the materials in all subjects, not only the ones they find more important to work on. Even though online classroom and online assignment are common in developed countries, in many developing countries, online classroom and online assignments are not possible due to limited access to the internet. But this is not the case for the protests in Thailand, because the protests occurred in the capital city where access to internet is not a problem. Therefore, in a country where internet access is not an issue, relying on the online classroom and online assignments can be a potential policy recommendation to lessen the adverse impact of the political unrest on test scores.

One limitation of this study is that the estimations are done at the school level because individual level data are not available. Future research can be extended to the individual level to provide more insightful findings. In addition, the size and the direction of the impact of the political protests could vary and potentially depend on the geographic locations or continents. Similar works conducted in different countries or geographic locations where local political protests interrupt schooling will provide comparable measures to my findings and will allow me to generalize my results to other settings.

Chapter 2

THE IMPACTS OF NATURAL DISASTER ON STUDENT ACHIEVEMENT: EVIDENCE FROM SEVERE FLOODS IN THAILAND

2.1 Introduction

Natural disasters have become more frequent in the past decade according to the Emergency Events Data Base (EM-DAT) maintained by the Centre for Research on the Epidemiology of Disasters (CRED**)**. Over 300 natural disasters affected more than 140 million people in 2014 alone (Guha-Sapir, Below, and Hoyois 2016). Figure 2.1 shows the total number of reported natural disasters per disaster type between 1990 and 2016 (CRED 2016).

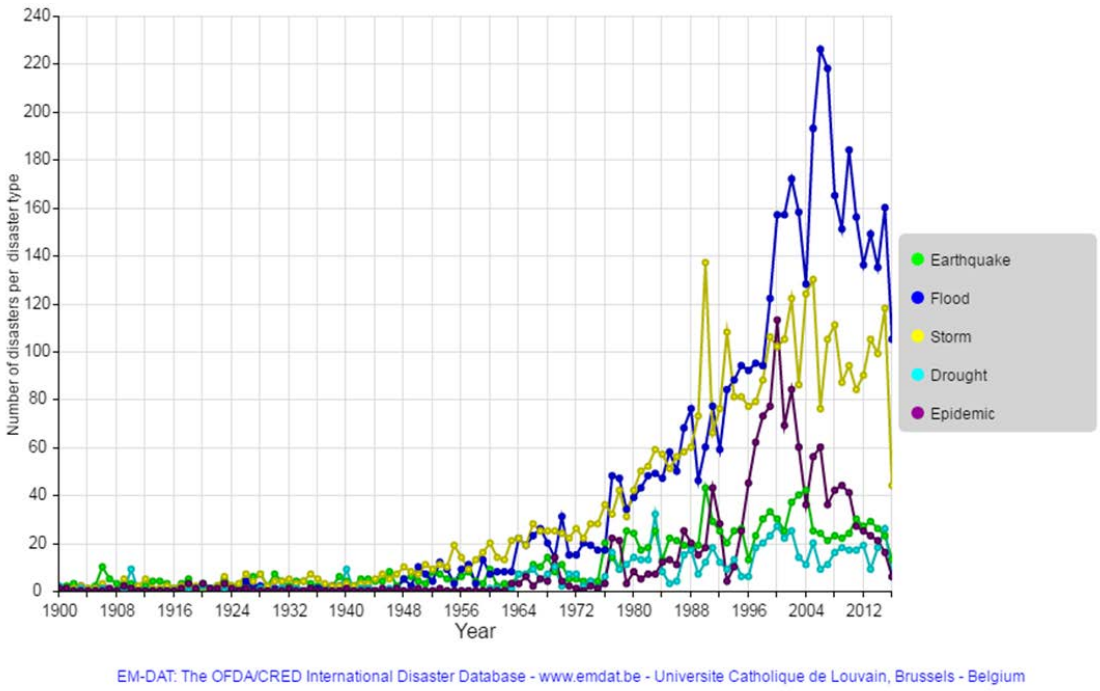


Figure 2.1: Total Number of Reported Natural Disasters between 1990 and 2016 (CRED 2016)

As shown in Figure 2.1, the reported number of five major types of natural disaster — earthquake, flood, storm, drought and epidemic— are increasing. Developing countries are often less able to mitigate the effects of such disasters. While much of the existing literature focuses on the contemporaneous impacts of natural disasters on growth and poverty, little is known about the impact of natural disasters on student achievement, an important input into later growth and development. Since flood is the type of natural disaster that occurred most frequently in the past decade, this study seeks to fill the gap by estimating the impact of severe flooding on student achievement, using a unique natural experiment in Thailand.

Severe flooding impacts student performance through four different channels. First, students might lose days of schooling because of school closures. Second, some students might have to miss more classes if their homes are damaged because of the floods. Third, many researchers have shown that students develop stress symptoms after they experienced disasters (Galea, Nandi, and Vlahov 2005; La Greca and Silverman 2009; La Greca, Silverman, and Wasserstein 1998; Kemp et al. 2011; Ceyhan and Ceyhan 2007). Stress also interrupts student academic performance (Saigh, Mroueh, and Bremner 1997; Kemp et al. 2011). Disasters not only cause impacts on mental health, but also cause physical health concerns such as malaria or dengue fever that directly affect student learning outcomes. Fourth, school infrastructure and resources are destroyed when floods occur. The losses of school resources and infrastructure could affect academic performance.

To evaluate the impact of severe flooding on student achievement, I take advantage of the flood that occurred in Thailand in 2011. The flood lasted from August 2011 until December 2011 and is ranked as the country's most damaging flood to date. Additionally, this flood is ranked as the world's most damaging natural disaster since 1900 (Guha-Sapir, Below, and Hoyois 2016). The damage caused by the 2011 flood is approximately $40 billion. The 2011 flood provides a unique natural experiment. Since not all provinces in Thailand were affected by this severe flooding, this setting naturally separates provinces into treatment and control groups. Schools in the flooded areas were temporarily closed for weeks, while schools in other areas remained open. I treat schools in the provinces that are unaffected from the flood as a control group.

My primary outcome of interest is the school level national standardized examination scores, the O-net examination scores, as a proxy for student academic achievement. I combine the school-level O-net examination scores from the National Institute of Educational Test Service (NIETS) with school specific data from the Ministry of Education for the academic year 2006-2013. The variation in the impact of the severe flooding allows me to use the difference-in-differences approach to estimate the impact of the flood on the O-net examination scores. My estimates suggest that the flood had a negative and significant impact on all test scores for grade 6, except social studies, and all test scores for grade 9, and on social studies test scores for grade 12. The impact of the flood on grade 6 social studies test scores is positive and significant. The magnitudes of the impact of the flood on test scores range from 0.03 to 0.11 standard deviations, depending on the subject and the level.

My work contributes to two strands of literature. First, it provides the first empirical evidence of the impact of the 2011 severe flooding in Thailand on student achievement. So far, researchers have explored the impact of this severe flooding on GDP growth, household income and expenditure, export, and investment (Chongvilaivan 2012; Poaponsakorn and Meethom 2013; Haraguchi and Lall 2014). No research has been done to investigate the impact of the 2011 flood on student achievement, even though this flood is ranked as the world's most damaging natural disaster since 1900 and caused a large disruption to schooling. Second, within the literature on disruption to schooling, my work provides evidence of the impact of an additional type of disruption: flooding. Earlier empirical works on student achievement studied the impact of other types of disruptions such as bad weather, pollution, war, and earthquakes (Pietro 2015; Goodman 2014; Saigh, Mroueh, and

Bremner 1997; Ebenstein, Lavy, and Roth 2016). My study contributes to the limited literature estimating the impact of school disruption on student achievement. My estimates, which range from 0.03 to 0.11 standard deviations, depending on the subject and the levels of the students, are consistent with earlier works. For example, Goodman (2014) found that each absence induced by bad weather reduces math achievement by 0.05 standard deviations while Hansen (2011) found that an additional day with snow greater than 4 inches decreases test scores by .015 standard deviations.

My results provide convincing evidence of the adverse impact of severe floods on test scores. Given the importance of test scores for later education attainment, additional attention should be paid to test scores in the aftermath of natural disasters. Ebenstein, Lavy, and Roth (2016) reported that even random variation in test scores can influence a student's academic path and earnings potential.

The remainder of this chpater is organized as follows. Section 2.2 describes the background of the 2011 flood in Thailand. Section 2.3 reviews the findings of earlier studies investigating the impacts of natural disasters, other types of disruption to schooling, and stress on academic outcome. Section 2.4 outlines the empirical strategy. Section 2.5 describes the data. Section 2.6 presents the estimated impact of the 2011 flood on O-net examination score. Section 2.7 presents several specification checks. Section 2.8 concludes.

2.2 Background

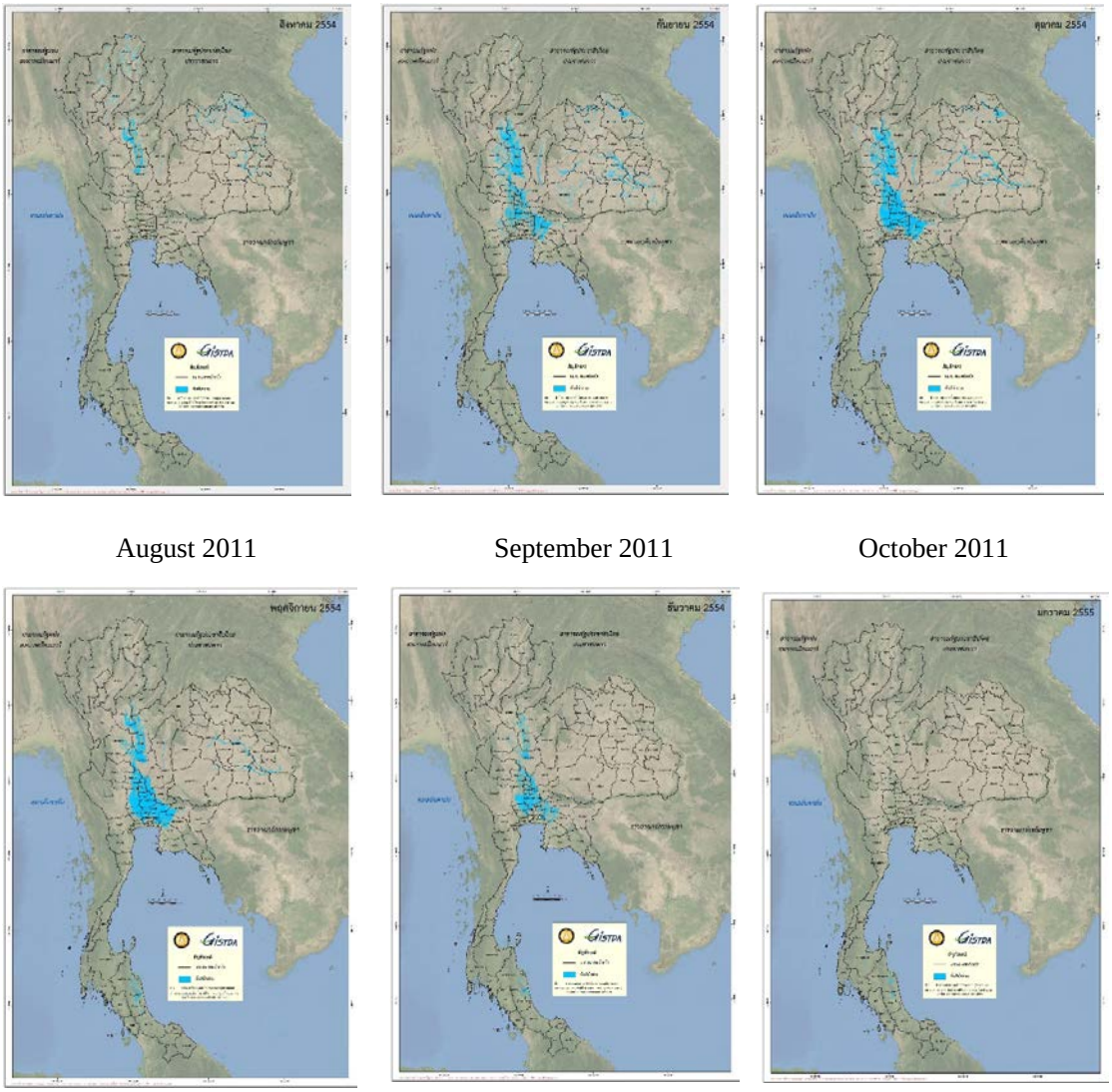
2.2.1 2011 Severe Flooding in Thailand

Thailand's tropical location and the effect of seasonal monsoon rains make Thailand prone to floods. From the middle of May to September is monsoon season in

Thailand. During the monsoon season, flash floods occur in many provinces. It usually lasts for only a few hours or days. However, the flood in 2011 lasted for months. It is ranked as the country's most damaging flood to date. The flood was a result of the exceptionally high rainfall during the 2011 monsoon season. The annual rainfall in 2011 was 24% above normal and was the highest in 61 years (Thai Meteorological Department 2015).

On July 31, 2011, the tropical storm "Nock-Ten" originated in the South China Sea, moved over Vietnam and Laos, and headed to the northern and northeastern parts of Thailand. The storm caused widespread heavy rains in many provinces (Thai Meteorological Department 2015). Between July and October 2011, several more storms went over Thailand. The abundant rainfall caused many provinces to be flooded for months. Figure 2.2 and Figure 2.3 provide the areas and the timeline that were affected by the flood.

The 2011 flood disrupted the daily life of children in schools. The schools in the flooded areas needed to be closed for weeks or even a month. Textbooks, computers and many other school resources were destroyed because of the flood. But the flood in 2011 did not affect all provinces in Thailand. This situation creates the variation in the impact of the floods. This setting naturally provides me the treatment and control groups for my study. As shown in Figure 2.2, schools in the areas that were flooded are treated as a treatment group in my study.



August 2011 September 2011 October 2011

November 2011 December 2011 January 2012

Figure 2.2: Areas Affected by the 2011 Flood (Thailand Flood Monitoring System 2015)[6]

[6] Geo-Informatics and Space Technology Development Agency (GISTDA) has created the Thailand flood monitoring system. Thailand Flood Monitoring System, http://flood.gistda.or.th/, provides both real-time and historical flood data.

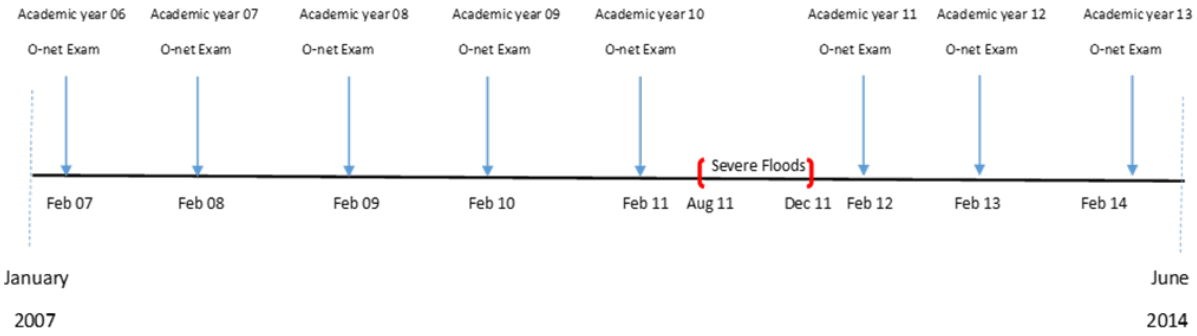


Figure 2.3: Timeline of Thailand 2011 Flood

2.3 Literature Review

2.3.1 Natural Disasters and Academic Performance

The unexpected nature of the natural disasters makes them challenging for researchers to estimate their impacts. Since natural disasters occur unexpectedly, in most cases researchers have no chance to establish measurements of student performance prior to the disasters. Nevertheless, many researchers have studied the effect of different types of natural disasters on academic performance.

One type of natural disaster that many researchers have tried to identify the impact of is an earthquake. Ceyhan and Ceyhan (2007) studied the impact of the earthquakes in Marmara, Turkey, on earthquake survivors' academic achievements six years after the earthquakes. They collected data from 407 Turkish university students. Of these, 201 were earthquake survivors and the rest had not been exposed to an earthquake. They found that the academic achievement of earthquake survivors was lower than those of individuals who were not exposed to an earthquake.

Pietro (2015) studied the impact of the earthquake that hit the city of L'Aquila in 2009 on the academic performance. He used a difference-in-differences framework

to estimate the impact of the L'Aquila earthquake on drop out and on-time graduation. He compared changes in drop-out and on-time graduation among students of the University of L'Aquila before and after the earthquake with changes in graduation status at the same time period among students enrolled at other Central Italian universities. He found that the L'Aquila earthquake reduced students' probabilities of graduating on time by 6.6 percentage points, and it had no statistically significant effect on university dropout in the short-term. In addition, Kemp et al. (2011) studied the impact of the earthquake that struck Christchurch in September 2010 on academic performance. They found that there was no significant negative impact of the earthquake on student performance.

Researchers have also studied the impact of hurricanes on student performance. Watson, Loffredo, and McKee (2011) investigated the impact of Hurricane Ike that struck Galveston Island in 2008 on the students of the University of Texas Medical Branch (UTMB). The authors conducted a Hurricane Needs Survey (NHS). They found that almost half of the respondents reported that the hurricane had negatively affected their academic performance. In contrast, Krane, DiCarlo, and Kahn (2007) analyzed the impact of Hurricane Katrina that ravaged the Mississippi and Louisiana Gulf in 2005 on the medical program of Tulane University School of Medicine and Louisiana State University School of Medicine at New Orleans. Major educational and teaching facilities of both schools were flooded following the storm. They relocated their training programs to new locations and reestablished training for students and residents 1 month later. Hurricane Katrina seemed to have no impact of student performance because student performance, as measured by mean final course average, standardized course examination scores from the National Board of Medical

Examiners, and scores for United States Medical Licensing Examination Step 1 and 2, were all unchanged.

2.3.2 Other Types of Interruption and Academic Performance

The existing literature has studied many other different types of interruptions that can affect academic performance. Bad weather is one of the most common interruptions. Marcotte (2007) studied the impact of instructional time on test scores. He took advantage of variation in winter weather that made non-trivial differences in the number of school days students received prior to taking the Maryland School Performance Assessment Program (MSPAP) exams. He found that students who took exams in years with heavy snowfall performed significantly worse than their peers in the same school who took MSPAP exams in the other years. He concluded that education inputs in the form of instructional days improved students' test scores. Marcotte and Hemelt (2008) studied whether unscheduled school closings lowered student performance or not. Their identification strategy is based on the fact that math and reading assessments were administered on the same day in Maryland, and any unscheduled closings due to snow reduced instruction time, and were not made up until after the exams were over. They found that losing school days to unscheduled closings had negative effects on performance. They also found that school closings had larger effects on performance for students in lower grades. Hansen (2011) estimated the causal impact of school year length on student performance using variation of instructional time from weather-related cancellations in Colorado and Maryland. He found that more instructional time prior to test administration increased student performance.

Goodman (2014) studied the impact of instructional time lost due to absences, as well as to school closures, on achievement. He found that there was a strong relationship between student absences and achievement but there was no relationship between school closures and achievement. Since prior works (Marcotte 2007; Marcotte and Hemelt 2008; Hansen 2011) argued that bad weather could serve as an instrument for the number of snow days experienced by a given school or student — allowing identification of the impact of snow days, Goodman showed that bad weather violated the exclusion restriction because bad weather affected not only school closures but also student absences. He found that all of the impact of weather ran through student absences and none through school closures. Thus, he claimed that his paper provided some of the first well-identified evidence on the impact of student absences on achievement.

Ebenstein, Lavy, and Roth (2016) studied the impact of pollution on student achievement. They found that exposure to pollution during high-stakes examinations is associated with a decline in student performance on the Israeli national examination. Moreover, they found that variation in test scores induced by pollution had a significant effect on long-term education attainment and adult wages.

Not only natural disasters or bad weather can disrupt student learning, but man-made disasters or community traumatic events such as mass shootings, wars, or terrorist attacks can also disrupt student learning. These events can reduce instructional time by causing teacher and student absences and school closures. Gershenson and Tekin (2015) used the 2002 “Beltway Sniper” attacks as the source of variation in attendance. They used difference-in-differences strategy to identify the causal impact of the Beltway sniper on student achievement in Virginia’s public

schools. They found that the attacks significantly reduced academic performance in schools within five miles of an attack.

Saigh, Mroueh, and Bremner (1997) studied the impact of war in Lebanon on academic performance. The study found that the Metropolitan Achievement Test (MAT) scores of students who developed post-traumatic stress disorder (PTSD) after they had been exposed to highly stressful incidents throughout Lebanon in 1991 were significantly lower than students who did not meet the criteria for PTSD. However, Smilde-van den Doel, Smit, and Wolleswinkel-van den Bosch (2006) found that school children who were exposed to firework explosions in the Netherlands performed no worse than children who were not exposed to the disaster.

2.3.3 The Effect of Stress on Academic Performance

Disasters and other types of school interruptions not only cause student absences or school closures, but they also make students develop stress symptoms (Galea, Nandi, and Vlahov 2005; La Greca and Silverman 2009; La Greca, Silverman, and Wasserstein 1998; Kemp et al. 2011; Ceyhan and Ceyhan 2007). Studies have connected severe symptoms such as PTSD with declines in academic performance (Kemp et al. 2011; Saigh, Mroueh, and Bremner 1997).

2.4 Empirical Strategy

Estimating the impact of flooding is challenging partly due to the short duration of most floods. However, the flood in Thailand in 2011, which lasted for several months, allows me to estimate the effect of a severe flood on student achievement. I exploit the exogenous change in student achievement, using a difference-in-differences strategy. The first difference compares schools in provinces

that were affected by the flood and schools in provinces that were not affected by the flood. The second difference compares the timing of the flood. The difference in these differences can be interpreted as the causal effect of the flood on the O-net examination scores. I define the treatment group as the schools that were affected by the 2011 severe flood. I define school *s* as being affected by the 2011 flood if the school *s* is flooded anytime between August 2011 and December 2011. Then I estimate the impact of the floods as follows:

$$Score_{st} = \alpha + \beta(Flood2011_{st}) + \lambda(EverFlooded_s \times Trend_t) + \delta_s + \delta_t + \varepsilon_{st} \quad (2.1)$$

where $Score_{st}$ is the school level O-net examination score (i.e., overall average score, subject specific test score) of school *s* in academic year *t*; $Flood2011_{st}$ is a dummy variable that takes the value of 1 if the school *s* was affected by the flood and the academic year *t* is 2011, and 0 otherwise; $EverFlooded_s$ is a dummy variable that takes the value of 1 if the school *s* was affected by the 2011 flood, and 0 otherwise; $Trend_t$ is a time trend variable; δ_s are school fixed effects that represent an individual school's unobserved time invariant characteristics; δ_t are academic year fixed effects; ε_{st} is the idiosyncratic error term. Since the flood occurred between August 2011 and December 2011 as shown in Figure 2.3, the impact of the flood should show up on the O-net examination scores in academic year 2011. This is why the dummy variable, $Flood2011_{st}$ takes the value of 1 only when academic year *t* is 2011. The interaction of $EverFlooded_s \times Trend_t$ allows flooded schools and control schools to follow different linear time trends. Since the flooded schools are located in a central part of Thailand, these flooded schools tend to have better resources such as better teachers and modern

facilities than control schools located in the rural areas. Equation (2.1) presumes that in the absence of a flood, the change in test scores of the treated schools deviate from common year fixed effects by following the linear trend captured by λ. The specifications as in equation (2.1), difference-in-differences strategy with time trends, are equivalent to an interrupted time series (ITS) approach in education research (Bloom 2003).

In this baseline model, β is the parameter of interest. β is the effect of the flooding on the O-net examination scores. If a severe flood adversely affects the O-net examination scores, the test scores of schools that were affected by the flood should be lower than those of the schools that were not affected by the flood. Equation (2.1) is estimated using Ordinary Least Squares (OLS). Since the estimation of equation (2.1) might suffer from the potential autocorrelation, ignoring the potential autocorrelation and using the conventional standard errors are likely to yield misleading statistical conclusions. I correct for the potential autocorrelation by clustering the standard errors at the school level.

Even though in equation (2.1), I include school-specific fixed effects to control for unobserved time-invariant characteristics of the schools, the challenge relevant to my estimation is to account for omitted variables that are time-varying. To account for potential selection bias, I estimate additional specifications that include additional time-varying school-specific covariates in the robustness checks section.

2.5 Data

My data combine three primary data sources— the school-level O-net examination scores from academic year 2006 to academic year 2013, school specific data, and flood data. The school-level O-net examination scores are from the National

Institute of Educational Test Service (NIETS). The data contain the average O-net scores of each primary and secondary school in Thailand from academic year 2006 to academic year 2013.

I combine the O-net scores data with school specific data from the Ministry of Education that contain the number of students enrolled, student teacher ratio, number of teachers, and number of students by gender and by grade for academic years 2006-2013. I exclude special schools that do not follow the standard curriculum such as international schools and religious schools. Students of these schools are not required to take the O-net examination.

The flood data come from Geo-Informatics and Space Technology Development Agency (GISTDA), a public organization founded by of the Ministry of Science, Technology and Environment. GISDTA created the Thailand Flood Monitoring System. As shown in Figure 2.2, GISDTA collects and maintains satellite data on its website, Thailand Flood Monitoring System. In order to precisely identify schools that were affected by the flood, I collected the latitude and longitude of all schools in my sample. I generated the treatment variable, *EverFlooded*, based on the flood map from GISDTA and schools' GPS locations.

Even though the O-net examination consists of 8 subjects, in this analysis, I limit my attention to only 5 core subjects (Thai, social studies, science, mathematics, and English) because of the completeness of the data. I fit equation (2.1) with the test scores data from these 5 core subjects and report the findings in the results section. In

addition to the 5 core subjects, I also estimate equation (2.1) using overall average scores and core average scores as additional dependent variables. [7,8]

Table 2.1 presents some sample descriptive statistics. In Table 2.1, *flooded* schools are defined as in equation (2.1). Panels A, B, and C of Table 1 present the average O-net examination scores of *flooded* schools and *control* schools by subject and by level. Table 2.1 shows that the levels of academic performance of *flooded* schools and that of *control* schools are similar.

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[7] To get the overall average score of school *s* in year *t*, I divide the sum of all test scores by the number of exams that are administered in year *t*. In academic year 2006, only Thai, social studies, mathematics, English and science examinations were administered for grade 12 students. Therefore, the grade 12 overall average score in year 2006 is the average of these 5 subjects. But in all other years, the grade 12 overall average score is the average of the test scores of all 8 subjects.

[8] For grade 9 and grade 12, the core subjects include Thai, social studies, science, mathematics, and English. Thus, the core average score for grade 9 and grade 12 is the average of the test scores of these core subjects. For grade 6, the core subjects include only Thai, science, and mathematics because in the first two years of O-net examinations grade 6 students were required to take only these three subjects.

Table 2.1: Descriptive Statistics

Panel A. Grade6							
	Overall Average Score	Core Average Score	Thai	Social Studies	Mathematics	English	Science
Flooded Schools	44.68	41.73	41.15	43.01	41.85	30.98	42.18
	(7.81)	(8.90)	(9.15)	(9.96)	(12.66)	(13.29)	(10.29)
Observations	23045	23045	23045	16432	23045	16432	23045
Control Schools	43.08	40.34	40.03	41.63	40.20	30.44	40.78
	(8.10)	(9.10)	(9.39)	(10.25)	(12.86)	(13.09)	(10.22)
Observations	196065	196065	196065	140038	196065	140038	196065
Panel B. Grade9							
	Overall Average Score	Core Average Score	Thai	Social Studies	Mathematics	English	Science
Flooded Schools	37.82	33.78	43.01	40.60	26.90	25.77	32.60
	(5.09)	(5.71)	(7.75)	(6.04)	(6.62)	(8.84)	(6.96)
Observations	6909	6909	6909	6909	6909	6909	6909
Control Schools	37.42	33.61	42.45	40.00	27.08	25.80	32.70
	(5.47)	(6.09)	(8.05)	(6.45)	(7.44)	(9.05)	(7.36)
Observations	60157	60157	60157	60157	60157	60157	60157

Table 2.1 continued.

Panel C. Grade12							
	Overall Average Score	Core Average Score	Thai	Social Studies	Mathematics	English	Science
Flooded Schools	35.20	30.86	43.39	34.66	22.99	23.58	29.70
	(5.37)	(5.73)	(7.93)	(5.97)	(8.33)	(7.48)	(4.74)
Observations	2818	2818	2818	2818	2818	2818	2818
Control Schools	33.93	29.64	41.37	33.84	21.88	22.13	28.99
	(4.93)	(5.15)	(7.31)	(5.63)	(7.72)	(6.71)	(4.23)
Observations	22370	22370	22370	22370	22370	22370	22370

2.6 Results

Table 2.2 presents initial evidence of the impact of the flood. Table 2.2 reports the difference in sample means of treated schools and control schools before and after the 2011 floods, by subject and by student level. In addition, Table 2.2 reports the sample difference-in-differences estimates which are the differences between the difference in sample means of treated schools and control schools. The sample difference-in-differences estimates in Table 2.2 suggest that the flood had a *negative* impact on all test scores for grade 6 except social studies and English, all test scores for grade 9 and *only* social studies test scores for grade 12. Since the differences in sample means shown in Table 2.2 are likely to suffer from omitted variable bias, I fit equation (2.1) with test score data by subject and by level.

Table 2.2: Difference in Means

	Grade 6			*Grade 9*			*Grade 12*		
	Prior to 2011	2011	Difference	Prior to 2011	2011	Difference	Prior to 2011	2011	Difference
Overall Average Score									
Treatment	43.422	49.513	6.091	35.517	40.582	5.064	35.563	33.524	-2.040
	(7.500)	(8.153)		(4.535)	(5.081)		(5.106)	(3.849)	
Control	41.860	48.381	6.521	35.020	40.522	5.501	34.395	32.027	-2.368
	(7.890)	(8.862)		(4.874)	(5.684)		(4.482)	(3.624)	
			-0.430			-0.437			0.329
Core Average Score									
Treatment	41.055	47.644	6.589	31.800	36.738	4.938	32.012	27.708	-4.304
	(7.838)	(8.793)		(4.913)	(5.493)		(5.629)	(4.225)	
Control	39.571	46.996	7.425	31.504	37.036	5.531	30.811	26.427	-4.384
	(8.198)	(9.592)		(5.329)	(6.197)		(4.862)	(3.758)	
			-0.836			-0.594			0.080
Thai									
Treatment	37.061	49.922	12.861	38.498	47.377	8.879	43.411	39.865	-3.545
	(6.572)	(8.554)		(4.991)	(6.194)		(8.085)	(5.320)	
Control	36.065	49.216	13.151	37.883	47.254	9.371	41.433	37.825	-3.608
	(6.967)	(9.530)		(5.329)	(6.823)		(7.186)	(5.210)	
			-0.290			-0.492			0.063

Table 2.2 continued.

	Grade 6			*Grade 9*			*Grade 12*		
	Prior to 2011	2011	Difference	Prior to 2011	2011	Difference	Prior to 2011	2011	Difference
Social Studies									
Treatment	40.298	52.512	12.214	39.509	42.487	2.978	35.967	31.889	-4.078
	(5.432)	(8.744)		(5.341)	(6.298)		(4.942)	(3.077)	
Control	39.190	50.765	11.575	38.751	42.273	3.522	35.106	31.164	-3.942
	(5.887)	(9.677)		(5.718)	(6.989)		(4.375)	(2.898)	
			0.638			-0.544			-0.136
Mathematics									
Treatment	40.876	52.620	11.745	26.831	31.567	4.736	25.265	20.168	-5.097
	(10.744)	(12.593)		(6.152)	(5.994)		(5.911)	(5.438)	
Control	39.226	51.575	12.349	26.874	32.422	5.548	24.169	19.069	-5.099
	(11.095)	(13.383)		(6.977)	(7.498)		(5.000)	(4.603)	
			-0.605			-0.813			0.002
English									
Treatment	25.029	37.246	12.217	22.733	30.314	7.581	25.094	20.314	-4.779
	(13.045)	(13.010)		(7.688)	(7.129)		(6.209)	(5.949)	
Control	25.379	37.022	11.643	22.579	30.848	8.269	23.799	18.563	-5.236
	(13.986)	(13.261)		(7.940)	(7.452)		(5.058)	(4.541)	
			0.574			-0.687			0.457
Science									
Treatment	45.229	40.388	-4.840	31.428	31.943	0.515	30.324	26.301	-4.023
	(9.316)	(8.556)		(6.162)	(6.744)		(4.918)	(3.243)	
Control	43.422	40.196	-3.226	31.435	32.382	0.948	29.550	25.515	-4.035
	(9.751)	(9.195)		(6.753)	(7.679)		(4.257)	(2.962)	
			-1.614			-0.432			0.012

Table 2.3 presents the estimates of equation (2.1). Panels A, B, and C of Table 3 report the estimates when fitting equation (2.1) with grade 6, grade 9, and grade 12 O-net examination scores, respectively. Columns 1-7 of each panel contain the estimates when the dependent variables are overall average scores, core average scores, and subject specific test scores, respectively. Standard errors clustered at the school level appear in parentheses.

Table 2.3: Effect on O-net Examination Scores, Equation (2.1)

	Dependent Variable						
	Overall Average Score (1)	Core Average Score (2)	Thai (3)	Social Studies (4)	Math (5)	English (6)	Science (7)
Panel A: Grade 6							
Flood2011	-0.481***	-0.723***	-0.523***	0.458***	-0.624***	-0.406**	-1.024***
	(0.130)	(0.139)	(0.147)	(0.145)	(0.195)	(0.202)	(0.146)
Observations	219110	219110	219110	156470	219110	156470	219110
Adjusted R-square	0.176	0.325	0.484	0.542	0.363	0.278	0.364
Panel B: Grade 9							
Flood2011	-0.392***	-0.550***	-0.511***	-0.466**	-0.826***	-0.568***	-0.379**
	(0.135)	(0.144)	(0.166)	(0.184)	(0.169)	(0.182)	(0.188)
Observations	67066	67066	67066	67066	67066	67066	67066
Adjusted R-square	0.381	0.442	0.703	0.245	0.343	0.554	0.345
Panel C: Grade 12							
Flood2011	0.0580	-0.0556	-0.126	-0.213**	-0.0802	0.0419	0.0999
	(0.0723)	(0.0750)	(0.164)	(0.0882)	(0.103)	(0.0978)	(0.0810)
Observations	25188	25188	25188	25188	25188	25188	25188
Adjusted R-square	0.692	0.701	0.458	0.833	0.923	0.880	0.489

Table 2.3 Continued

Notes: All regressions include school and year fixed effects. Values of robust standard errors clustered at school level appear in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

2.6.1 Grade 6

All regressions in Panel A of Table 2.3 indicate statistically significant effects of the flood on grade 6 test scores. The flood had a negative and significant effect on overall average scores, core average scores, and the test scores for Thai, mathematics, English, and science. The impact on social studies is positive and significant. The point estimate in column 1 of Table 2.3 indicates that the flood in 2011 is associated with a decline in grade 6 overall average scores by 0.481 points, equivalent to a 0.060 standard deviation decline in overall average scores. The result in column 2 implies that the flood is associated with 0.723 points or a 0.080 standard deviation decrease in grade 6 core average scores. In column 3, the flood lowers Thai test scores by 0.523 points or 0.060 standard deviations. However, the point estimate in column 4 indicates that schools that were affected by the flood in 2011 outperform the schools that were not affected by the flood by 0.458 points or 0.045 standard deviations.

In contrast to column 4, the point estimates in column 5 and 6 imply that being affected by the flood in 2011 is associated with the drop in mathematics and English test scores by 0.624 points or 0.049 standard deviations, and by 0.406 points or 0.031 standard deviations, respectively. The impact of the flood on science O-net Examination scores is largest on science test scores. The result in column 7 implies that the flood is associated with 1.024 points or a 0.100 standard deviation decrease in grade 6 science test scores. Since science is a subject that requires experimentation in the classroom, young learners such as those in grade 6 might have found it harder to study on their own while schools were closed because of the flood. In addition, grade 6 students might have had difficulty catching up with the material when schools reopened. Unlike social studies or languages, topics in science are built upon one

another. Therefore, it might have been harder for teachers to squeeze all required topics in a limited time period because the examination date was scheduled earlier in the academic year, and was not postponed.

2.6.2 Grade 9

All regressions in Panel B of Table 2.3 indicate statistically significant negative effects of the flood on grade 9 test scores. For example, the point estimate in column 1 indicates that the flood in 2011 is associated with a decline in grade 9 overall average scores by 0.392 points, equivalent to a 0.07 standard deviation decline. Moreover, the result in column 2 implies that the flood is associated with 0.550 points or a 0.09 standard deviation decrease in core average scores. In column 3, the flood lowers Thai test scores by 0.511 points or 0.060 standard deviations. Contrary to the impact on grade 6 social studies test scores, the point estimate in column 4 in panel B indicates that the impact of the 2011 flood is associated with a decline in grade 9 social studies test scores by 0.466 points or 0.07 standard deviations. Unlike grade 6 students, grade 9 students are more independent, so it might have been more difficult for parents to encourage them to study on their own when schools were closed. This might help explain why the direction of the impact of the 2011 flood on social studies test scores is opposite to that of grade 6. The point estimates in column 5 and 6 of Table 3 imply that being affected by the flood in 2011 is associated with the drop in mathematics and English test scores by 0.826 points or 0.112 standard deviations, and by 0.568 points or 0.06 standard deviations, respectively. The result in column 7 implies that the flood lowers Science test scores by 3.79 points or 0.05 standard deviations.

2.6.3 Grade 12

Only the coefficient in column 4 in Panel C of Table 2.3 indicates statistically significant effects of the flood on grade 12 test scores. The flood had a negative and significant effect only on grade 12 social studies test scores. The point estimate in column 4 indicates that the flood in 2011 is associated with a decline in grade 12 social studies test scores by 0.213 points, equivalent to a 0.04 standard deviation decline. Since the O-net examination score is one of the requirements for university entrance applications, grade 12 students in academic year 2011 have an incentive to work as hard as grade 12 students in other academic years despite the loss of instructional time due to the flood. Even though schools were closed, because grade 12 students took this exam more seriously than grade 6 and grade 9, they might have had to stick with their study plans for the O-net examination, and other examinations (GAT and PAT examinations) , which were all scheduled after the flood as much in academic year 2011 as in any other year. This might be a potential explanation why the impact of the 2011 flood on grade 12 O-net examination scores is insignificant in most cases. Moreover, grade 12 students are more mature than grade 9 and grade 6 students. Grade 12 students are more likely than grade 9 and grade 6 students to study on their own while they were away from schools. This also helps explain why the impact of the 2011 flood on most of grade 12 O-net examination scores is insignificant.

Furthermore, grade 12 students might have the incentive to focus more on subjects that have higher weight according to the university admission system.[9] The

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[9] Thailand central university admission system puts 20% weight on students' cumulative average GPA, 30% weight on O-net examination results, and 50% on GAT/PAT examination results. Student tend to take only GAT examination with other

central university admission system in Thailand requires students to submit their cumulative average GPA of their last 6 semesters, their O-net examination results, and their GAT and PAT test scores. As explained in chapter 1, GAT and PAT examinations, which are administered after the O-net examination, are optional. Students choose to take only GAT and specific PAT tests that are required for their future course of study. Unlike other subjects, social studies is not part of any GAT and PAT examinations. Thus, grade 12 students might find social studies to be less important than other subjects when they prepare for the O-net examination. This can potentially explain why the negative impact of the flood is significant only on social studies test scores.

2.7 Robustness Checks

Table 2.4 presents specification checks for grade 6 using variants of equation (2.1). Column 2 in Table 2.4 includes student-teacher ratios to control for a time-varying school-specific factor that is not captured by the inclusion of school fixed effects. In all cases, the results are all robust to the inclusion of the student-teacher ratio as an additional explanatory variable. All results in column 2 are similar to my baseline results in terms of size, direction, and level of significance.

PAT examinations that are required for their future course of study. For example, if a student is interested in applying to an engineering school, this student is required to take GAT, PAT-Math, and PAT-Engineer tests.

Table 2.4: Specification Check for Grade 6, Equation (2.1)

	Baseline (Table 2.3) (1)	Include student/teacher ratio (2)	Exclude Bangkok Schools (3)
Dependent variable: Overall Average Score			
Flood2011	-0.481***	-0.530***	-0.313**
	(0.130)	(0.131)	(0.141)
Observations	219110	213126	213162
Adjusted R-square	0.176	0.174	0.175
Dependent variable: Core Average Score			
Flood2011	-0.723***	-0.777***	-0.534***
	(0.139)	(0.140)	(0.150)
Observations	219110	213126	213162
Adjusted R-square	0.325	0.324	0.322
Dependent variable: Thai			
Flood2011	-0.523***	-0.592***	-0.424***
	(0.147)	(0.148)	(0.159)
Observations	219110	213126	213162
Adjusted R-square	0.484	0.480	0.479
Dependent variable: Social Studies			
Flood2011	0.458***	0.396***	0.489***
	(0.145)	(0.146)	(0.158)
Observations	156470	152514	152237
Adjusted R-square	0.542	0.542	0.536
Dependent variable: Mathematics			
Flood2011	-0.624***	-0.682***	-0.361*
	(0.195)	(0.197)	(0.211)
Observations	219110	213126	213162
Adjusted R-square	0.363	0.363	0.360
Dependent variable: English			
Flood2011	-0.406**	-0.548***	-0.146
	(0.202)	(0.202)	(0.218)
Observations	156470	152514	152237
Adjusted R-square	0.278	0.273	0.274

Table 2.4 continued.

	Baseline (Table 2.3) (1)	Include student/teacher ratio (2)	Exclude Bangkok Schools (3)
Dependent variable: Science			
Flood2011	-1.024***	-1.056***	-0.816***
	(0.146)	(0.147)	(0.158)
Observations	219110	213126	213162
Adjusted R-square	0.364	0.363	0.357

Notes: All regressions include school and year fixed effects. Values of robust standard errors clustered at school level appear in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Column 3 in Table 2.4 excludes schools located in Bangkok from the sample. Schools in Bangkok experienced prolonged protests in academic year 2010 which is one academic year prior to the flood. I exclude Bangkok schools from my sample to control for the potential lagged impact of the 2010 protests on grade 6 O-net examination scores. By excluding Bangkok schools from the sample, all results are robust. All results in column 3 have the same direction as my baseline results, even though the impact on English tests score becomes insignificant. Estimates in column 3 possibly become insignificant because of a smaller sample size, and fewer treated schools.

Table 2.5 reports specification checks for grade 9 using variants of equation (2.1). Table 2.5 follows the same format as Table 2.4. As shown in column 2, my baseline results are robust to the inclusion of student-teacher ratios as an additional explanatory variable. In column 3, excluding Bangkok schools from my sample does

not change the direction of my baseline results. However, three of seven estimates become statistically insignificant. As explained earlier, the estimates in column 3 might lose significance because of a smaller sample size, and fewer treated schools.

Table 2.5: Specification Check for Grade 9, Equation (2.1)

	Baseline (Table 2.3) (1)	Include student/teacher ratio (2)	Exclude Bangkok Schools (3)
Dependent variable: Overall Average Score			
Flood2011	-0.392***	-0.452***	-0.240
	(0.135)	(0.134)	(0.149)
Observations	67066	64140	64791
Adjusted R-square	0.381	0.376	0.381
Dependent variable: Core Average Score			
Flood2011	-0.550***	-0.616***	-0.377**
	(0.144)	(0.143)	(0.159)
Observations	67066	64140	64791
Adjusted R-square	0.442	0.436	0.439
Dependent variable: Thai			
Flood2011	-0.511***	-0.551***	-0.356*
	(0.166)	(0.167)	(0.182)
Observations	67066	64140	64791
Adjusted R-square	0.703	0.699	0.701
Dependent variable: Social Studies			
Flood2011	-0.466**	-0.503***	-0.292
	(0.184)	(0.186)	(0.205)
Observations	67066	64140	64791
Adjusted R-square	0.245	0.241	0.242
Dependent variable: Mathematics			
Flood2011	-0.826***	-0.856***	-0.665***
	(0.169)	(0.170)	(0.187)
Observations	67066	64140	64791
Adjusted R-square	0.343	0.341	0.340

Table 2.5 continued.

	Baseline (Table 2.3) (1)	Include student/teacher ratio (2)	Exclude Bangkok Schools (3)
Dependent variable: English			
Flood2011	-0.568***	-0.691***	-0.403**
	(0.182)	(0.176)	(0.200)
Observations	67066	64140	64791
Adjusted R-square	0.554	0.549	0.553
Dependent variable: Science			
Flood2011	-0.379**	-0.478**	-0.168
	(0.188)	(0.187)	(0.209)
Observations	67066	64140	64791
Adjusted R-square	0.345	0.341	0.338

Notes: All regressions include school and year fixed effects. Values of robust standard errors clustered at school level appear in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Table 2.6 reports specification checks for grade 12 using variants of equation (2.1). Table 2.6 follows the same format as Table 2.4. Column 2 implies that all results except for science test score are robust to the inclusion of student-teacher ratios as an additional explanatory variable. The impact of the flood on grade 12 science test score becomes positive and statistically significant when adding student-teacher ratio as an additional explanatory variable. My baseline results are also robust to the exclusion of Bangkok schools from my sample as shown in column 3.

Table 2.6: Specification Check for Grade 12, Equation (2.1)

	Baseline (Table 2.3) (1)	Include student/teacher ratio (2)	Exclude Bangkok schools (3)
Dependent variable: Overall Average Score			
Flood2011	0.0580	0.0590	0.110
	(0.0723)	(0.0718)	(0.0750)
Observations	25188	23633	23580
Adjusted R-square	0.692	0.684	0.719
Dependent variable: Core Average Score			
Flood2011	-0.0556	-0.0472	0.0150
	(0.0750)	(0.0724)	(0.0711)
Observations	25188	23633	23580
Adjusted R-square	0.701	0.695	0.721
Dependent variable: Thai			
Flood2011	-0.126	-0.162	0.0785
	(0.164)	(0.162)	(0.171)
Observations	25188	23633	23580
Adjusted R-square	0.458	0.457	0.467
Dependent variable: Social Studies			
Flood2011	-0.213**	-0.210**	-0.0840
	(0.0882)	(0.0869)	(0.0919)
Observations	25188	23633	23580
Adjusted R-square	0.833	0.828	0.846
Dependent variable: Mathematics			
Flood2011	-0.0802	-0.0748	-0.0863
	(0.103)	(0.0988)	(0.0988)
Observations	25188	23633	23580
Adjusted R-square	0.923	0.921	0.930
Dependent variable: English			
Flood2011	0.0419	0.0808	0.0581
	(0.0978)	(0.0975)	(0.0815)
Observations	25188	23633	23580
Adjusted R-square	0.880	0.878	0.899

Table 2.6 continued.

	Baseline (Table 2.3) (1)	Include student/teacher ratio (2)	Exclude Bangkok schools (3)
Dependent variable: Science			
Flood2011	0.0999	0.131*	0.108
	(0.0810)	(0.0787)	(0.0827)
Observations	25188	23633	23580
Adjusted R-square	0.489	0.491	0.502

Notes: All regressions include school and year fixed effects. Values of robust standard errors clustered at school level appear in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

One potential concern in my analysis is the self-selection problem. As the flood in 2011 caused a huge disruption to local people including students, some students might not show up and take the O-net examination if they were displaced or were greatly impacted by the 2011 severe flooding. In Table 2.7, I examine this potential concern by replacing the dependent variable of equation (2.1) by the number of test takers in each level. The estimates from all regressions in Table 2.7 are statistically significant. Thus, there is evidence that the flood in 2011 led to a change in the number of test takers in all levels. This implies that the self-selection is likely to be a concern in my analysis. My analysis is done at the school level because I have no access to individual-level data. Thus, it's not possible for me to perform the Heckman two-stage correction for self-selection due to data limitations.

Table 2.7: Effect on Number of Test Takers

	Dependent variable: Number of Test Takers		
	Grade 6	Grade 9	Grade 12
	(1)	(2)	(3)
Flood2011	-0.413***	3.825***	-3.590***
	(0.118)	(0.522)	(0.981)
Regression statistics:			
Observations	219110	67066	25188
Adjusted R-square	0.131	0.082	0.120

Notes: All regressions include school and year fixed effects. Values of robust standard errors clustered at school level appear in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

2.8 Conclusion

In this chapter, I investigate the impact of severe flooding on student achievement. I take advantage of severe flooding in Thailand in 2011, which is ranked as the country's most damaging flood to date and as the world's most damaging natural disaster since 1900 (CRED 2016). The severe flooding in Thailand provides me with a unique natural experiment which allows me to employ a difference-in-differences approach. As reported in section 1, my estimates suggest that the flood in Thailand in 2011 is associated with a significant decline of all test scores for grade 6, except social studies, all test scores for grade 9, and only social Studies for grade 12. The flood in 2011 had a positive and significant impact on grade 6 social studies test scores. The magnitudes of the impact of the flood on grade 6, grade 9, and grade 12 test scores range from 0.03 to 0.11 standard deviations.

Even while flooding is the most frequent type of natural disaster that has occurred in the past decade, little is known about its impact on student achievement.

My work fills the gap in the existing literature by providing the first empirical evidence of the adverse impact of severe flooding on student achievement. Severe flooding can occur not only in developing countries like Thailand; developed countries are also at risk to experience severe flooding. My results highlight the negative impact of severe flooding on schooling, an important input into later growth and development.

Moreover, my findings provide additional evidence to the existing literature on the impact of disruptions to schooling on student achievement. My results suggest that additional support is needed to lower the adverse impact of severe flooding on high-stakes examinations like the O-net examination, because researchers found that a decrease in test scores can lead to lower educational attainment and earnings (Ebenstein, Lavy, and Roth 2016). Because my work captures only the short run impact of severe flooding on student achievement, future work can be extended to include the analysis of long-run consequences of the flood such as students' future earnings, and postsecondary educational attainment.

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