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Abstract

Random shocks to cognitive performance on high-stakes standardized tests have long-lasting consequences, particularly when test results are used as the sole mechanism to determine school admissions. This study considers the effects of exposure to local violent crime on high-stakes standardized test outcomes in the context of Mexico City's centralized high school admission system. To do so, we exploit within-school variation in exposure to local violent crime over time. Our results show that exposure to violent crime reduces test scores for female students but not for males, leading to a gender-biased high school placement. That is, female students' test scores decrease by 11 percent of a standard deviation after the exposure to violent crime occurring within 0.1 miles of their school during the week before the test, and approximately 19 percent of those students are assigned to less-preferred high schools than the ones to which they would have been assigned otherwise. The effect is highly localized both in time and geographic proximity, suggesting that temporary psychological harm is one of the main mechanisms through which exposure to violent crime affects cognitive performance.

Keywords: Violent crime; High-stakes tests; Gender inequality; Psychological well-being

JEL classification: I14, I21, I24, I25.

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1 Introduction

The nature of high-stakes exams makes random shocks to students' cognitive performance especially consequential. Though they may be taken long before students enter the workforce, high-stakes exams have the capacity to limit students' long-term human capital formation and weaken their lifetime labor and welfare outcomes (Ebenstein, Lavy, and Roth, 2016). It is because these exams are so economically significant that we must recognize how little is actually known about their capacity to equitably and accurately measure students' academic ability. This study documents the effect of exposure to local violent crime near testing dates on students' subsequent performance on high-stakes exams and its consequences on future education quality, joining a growing body of literature on the intangible costs of crime.

Much of this literature focuses on the effects of crime exposure on mental well-being outcomes, such as depression, anxiety and avoidance behaviors (Cornaglia, Feldman, and Leigh, 2014; Dustmann and Fasani, 2015); human capital formation (Barrera and Ibánez, 2004; Sharkey, 2010; Becker and Rubinstein, 2011; Rodriguez and Sanchez, 2012; Burdick-Will, 2013; Caudillo and Torche, 2014; Sharkey, Schwartz, Ellen, and Lacoe, 2014; Burdick-Will, 2016; Brown and Velásquez, 2017; Monteiro and Rocha, 2017; Casey, Schiman, and Wachala, 2018); and labor market outcomes (Dell, 2015; Velásquez, 2019). The costs of crime grow when we factor in potential long-lasting negative impacts and spillover effects. For example, Carrell, Hoekstra, and Kuka (2018) find that having peers who have been exposed to household domestic violence during elementary school reduces earnings in early adulthood. The associated reduction in the present discounted value of future earnings explains 5 percent of the earnings gap between the rich and the poor. Also, Cornaglia, Feldman, and Leigh (2014) find that the societal cost of increasing the crime rate by one additional victim is about 80 times higher than the direct cost on the victim.

Though high-stakes exam outcomes affect human capital formation in the long-run, they remain relatively understudied. Recent works analyzing this type of exam find that women underperform relative to men when the stakes are high, due to psychological pressure (Azmat, Calsamiglia, and Iriberri, 2016; Cai, Lu, Pan, and Zhong, 2019) and that random shocks affect cognitive performance in high-stakes tests (Ebenstein, Lavy, and Roth, 2016; Cho, 2017; Graff Zivin, Song, Tang, and Zhang, 2018; Park, 2018). Ebenstein, Lavy, and Roth (2016), in particular, find that ambient air pollution alters test performance, producing a noisy measure of student ability. This reduces both years of post-secondary education and monthly earnings in adulthood. Heissel, Adam, Doleac, Figlio, and Meer (2018), on the other hand, suggest high-stakes exams are rather a biased measure of student ability, as the noise they produce may not be evenly distributed across the socioeconomic spectrum.

Our work covers an otherwise unexplored dimension of the consequences of high-stakes exams—gender-biased measurement of students' academic ability and its effects on the allocation of human capital—by exploiting within-school variation in the timing of exposure to local violent crime occurring in close proximity to schools during the run-up to exam dates and estimating how violent crime exposure affects future education quality. The literature on the relationship between violent crime exposure and mental health indicates different psychological effects from crime by gender (Dustmann and Fasani, 2015); thus we allow our model to capture this linkage.

We perform our analysis in the context of Mexico City's centralized high school admission system. We consider Mexico City a natural setting for our analysis for two main reasons. First, the Metropolitan Area of Mexico City has the largest school system in Mexico. The growing demand for high-school education led to the implementation of an unusual annual high-stakes exam that is used as the sole means to assign students to public high schools. Second, violent crimes occur across school neighborhoods throughout Mexico City, providing ample geographical variation in crime exposure.

We use administrative records of crime reports and individual test scores from 2013 to 2016. The richness of our data and context provide several benefits in our analysis. First, we exploit the geographic coordinates of both crimes and schools to consider a set of different distances between the locations of various types of crimes and schools. Second, we make use of the exact timing of crimes to consider a set of different timings of exposure to crimes relative to the exam dates. This allows us to provide suggestive evidence on potential mechanisms through which exposure affects test scores. Another novelty of the data, which differentiates our study from the existing literature on the effects of random shocks on cognitive performance, is our access to students' revealed preference rankings of high schools prior to the exam and realized placements. Together with cutoff scores for each school in their priority list, we are able to quantify the share of misplaced students due to violent crime exposure. This illustrates how exposure to violent crime affects the allocation of human capital in the early stage of its development.

We find that exposure to violent crime reduces test scores and results in a poor matching between female students and high schools. Our estimates show that exposure to violent crime occurring within 0.1 miles of students' schools during the week before test dates reduces female students' test scores by approximately 11 percent of a standard deviation, while having no impact on males' test scores. This creates a significant gender gap in performance, which leads to a gender-biased allocation of female students into high schools. A back-of-the-envelope calculation suggests that approximately 19 percent of female students exposed to violent crime are assigned to less-preferred high schools than the ones to which they would have been assigned otherwise. In addition, we find that the effect is highly localized in both time and geographic proximity. The effect disappears as we expand the school neighborhood beyond 0.1 miles or increase the time-window of exposure to violent crimes up to four weeks prior to the test. This suggests that temporary psychological harm is one of potential mechanisms through which exposure to violent crime affects cognitive performance. Further, we show that the effects last longer for female students attending schools in relatively economically disadvantaged neighborhoods and are stronger for females attending schools in relatively safe ones.

The validity of our identification strategy could be compromised by non-random attrition, non-random selection, and systematic unobservable differences between students in schools that experience violent crime in close proximity of their schools and students in schools that do not experience such events. We provide evidence that attrition is not correlated with changes in exposure to violent crime, that our estimates are not driven by systematic differences across exposed and non-exposed students, and that our estimates are not driven by systematic changes on students' characteristics in treated schools.

The main results indicate that high-stakes entrance exams exacerbate gender inequality in education, since only female students are adversely affected by exposure to local violent crime. Moreover, our findings of larger effects on females in relatively safe school neighborhoods while having no impacts on females in high crime areas and on males, together suggest that adolescents who are repeatedly exposed to violent crimes are desensitized to such crimes to the degree that they do not affect test scores. In combination, our results shed light on potential policy interventions for closing the gender gap in educational outcomes and alleviating mental distress to reduce the societal costs of crime.

The rest of the paper proceeds as follows. Section 2 provides background on high-stakes exams in Mexico City; Section 3 describes the data; Section 4 describes the identification strategy; Section 5 presents empirical results; and Section 6 concludes.

2 Background

The public high school education system in the Metropolitan Area of Mexico City, which enrolls over 82 percent of all high school students, consists of nine subsystems that offer three different types of high school education: general, technological, and vocational. During the early 90s, the admission process to public high schools in this metropolitan area was highly inefficient. To apply to different subsystems of high schools, students had to complete multiple applications and take each school's entrance exam. After they were given admission at multiple schools in different subsystems, students had to choose their most preferred school and reject the others.

As a response to this inefficiency, in February of 1996, the nine different public high school subsystems in the Metropolitan Area of Mexico City signed a collaboration agreement and formed The Metropolitan Commission of Public Institutions of Higher Education (*Comisión Metropolitana de Instituciones Públicas de Educación Media Superior*, COMIPEMS), with the purpose of collectively and transparently meeting the increasing demand for public high-school education in the area. This meant having a unique pool of applicants and evaluating their skills and knowledge using a single metric.

To ensure impartiality, COMIPEMS administers an annual standardized test prepared by the National Center of Evaluation for Higher Education (*Centro Nacional de Evaluación para la Educación Superior*, CENEVAL), a non-profit association which offers evaluation services to several schools, universities, educational authorities, and government entities in Mexico. Every year the COMIPEMS exam takes place during the last weekend of June, either on Saturday or Sunday during the morning or the afternoon shift.[1] In 2016, more than 331,000 students started the application process, about 320,000 presented the admission exam, and 82 percent of those students were admitted in one of the more than 650 public schools in the metropolitan area.

[1] The academic calendar for 2015-2016 starts on August 24, 2015 and ends on July 15, 2016; and the 2016 COMIPEMS exam was administered on June 25-26, 2016. If the exam is administered after the school is officially over, then it creates a concern about our treatment—exposure to violent crimes occurring within 0.3 miles of the school in weeks before the test.

A distinctive feature of the COMIPEMS contest of assignment, as compared with other high-stakes tests around the world, is that the COMIPEMS exam is the sole determinant of admission into public high schools in Mexico City's metropolitan area. Also, test-takers' inability to alter testing date, place, or available capacity of high schools in any given year together provide us with an advantage in our identification strategy.

The assignment mechanism is based on students' school choices, test scores, and schools' capacity constraints. The assignment algorithm is as follows: (i) in February and March, ninth grade middle school students[2] send a priority list with up to 20 schools and complete a socio-demographic questionnaire; (ii) in June, students take the COMIPEMS test; (iii) in July, each public high school reports to COMIPEMS the maximum number of available seats in their school; (iv) students are ranked from the highest to lowest according to their test scores; (v) using a computerized algorithm, students are placed in their most-preferred high school with available seats. To break ties, a representative of each school decides whether the school offers admission to all or none of the students with the same score. The process runs until all seats are assigned.[3]

As the COMIPEMS test score is the sole means of high school admission, random shocks affecting student performance on the test can affect the probability of admission into public high schools and later higher education outcomes.

[2] Middle school in Mexico is 7th-9th grade, with an average age of 12-14; and high school is 10th-12th grades, with an average age of 15-17.

[3] For a more detailed description of COMIPEMS' assignment mechanism, see Bobba and Frisancho (2014), Estrada and Gignoux (2017), and Dustan, De Janvry, and Sadoulet (2017).

3 Data

Our analysis uses data that combine administrative records from the Ministry of Education, the Ministry of Public Security of Mexico City (SSP-CDMX), and the National Institute of Statistics and Geography (INEGI), which together bring a panel of schools with annual information at the student-level that spans from 2013 to 2016. The outcome variable is student test scores, and the treatment variables are different measures of exposure to violent crime prior to the test.

Student test scores are based on the admission exam of COMIPEMS, a centralized high school admissions system for all public high schools in the Mexico City Metropolitan Area. The COMIPEMS test consists of 128 equally-weighted multiple choice questions on different subjects, including math, math ability (reasoning), physics, biology, chemistry, verbal ability, Spanish, history, geography, and civics and ethics. To further explore the heterogeneous effects by subjects, we categorize each subject into two groups—(i) math and sciences and (ii) verbal and humanities.[4] In addition, the COMIPEMS data also contains information on student characteristics, including gender, graduation year, family background, neighborhood characteristics, and, most importantly, the middle school in which each student is enrolled at the time of the test. This information allows us to match each student with the different measures of exposure to violent crime occurring in close proximity of their middle schools around test dates. Furthermore, we observe each student's revealed preference ranking of high schools prior to the exam and her final placement at the end of the admission process.

[4] We normalize test scores from each year to have a mean of zero and a standard deviation of one. Math and sciences include math, math ability (reasoning), physics, chemistry, and biology; verbal and humanities include verbal ability (reasoning), Spanish, history, geography, and civics and ethics.

We match each school in student's priority list to its cutoff score for the corresponding year and compare this cutoff to both the realized score and its counterfactual to compute the fraction of students misplaced due to exposure to violent crime.

Our different measures of violent crime are based on administrative incident report records in Mexico City from SSP-CDMX between 2013 and 2016. Each incident contains information on the type of crime, date, time, and the geographic coordinates where the incident took place. The type of crimes include homicides, injuries with firearm, rapes, and various types of robbery and larceny. We define violent crime incidents as homicides and firearm injuries, which are the most salient and are more likely to be accurately reported.[5] Figure 1 shows the geographic distributions of the violent crimes that occurred within 4 weeks before each year's exam, along with the precise location of all middle schools. Note that violent crimes are distributed all over Mexico City, and there are both within-municipality and across-municipalities variation.[6] We focus our analysis on violent crimes occurring within 0.1, 0.2, and 0.3 radius miles of the middle schools where students are currently enrolled, illustrated by Figure 2. Violent crimes are linked to each school using the geographic coordinates of each middle school from the Ministry of Education. This enables us to identify the number of violent crimes that occurred within each category of the distances. We then define students' exposure to violent crime as attending schools that had at least one violent crime within 0.1 - 0.3 miles (approximately 1 to 5 city blocks) of their school during the

[5] In particular, we are worried that crimes, such as robberies and rapes, happening around schools located in higher-income neighborhoods are more likely to be reported; thus, the estimates would capture these socioeconomic differences instead. We use all other crimes in our secondary analyses.

[6] Figure A.1 and Figure A.2 in appendix A shows the geographic distribution of all violent and non-violent crimes from 2013 to 2016.

weeks prior to the COMIPEMS test date. It is important to note that unlike the United States, in Mexico City, 52 percent (53 for men and 51 for women) of middle school students walk to school and another 33 percent commute using public transportation, such as the metro and buses.[7] In doing so, most students are likely to be aware of the events happening in the immediate vicinity of their schools.

To consider heterogeneous effects of exposure to violent crime on the test scores, we also match each school to the 2010 urban poverty index and population of the Basic Geostatistical Area (*Área Geoestadística Básica*, AGEB) where the school is located.[8] This poverty index is a measure of social exclusion in terms of education, health, and housing characteristics. The index is calculated by the National Council of Population (CONAPO) based on information from the 2010 Population and Housing Census from INEGI.

The main analysis focuses on students taking the COMIPEMS exam between 2013 and 2016 who were enrolled in a middle school and residing in Mexico City at the time they took the test.[9]

4 Identification Strategy

We estimate the effects of violent crime on high-stakes tests using a difference-in-differences research design, which exploits within-school variation in exposure to violent crime over time. In particular, we focus on violent crimes occurring within 0.3 miles of schools before test

[7] These numbers are taken from INEGI's Daily Mobility Survey of *Encuesta Intercensal* 2015.

[8] An AGEB is a geographical area occupied by a set of blocks generally ranging from 1-50, perfectly bounded by streets, avenues, walkways or any other feature of easy identification in the field.

[9] We exclude those students who were re-taking the exam, and those who were commuting from municipalities outside of Mexico City.

dates. Our rationale for the 0.3 mile radius is that Casey, Schiman, and Wachala (2018), which examine the effect of violent crimes on school-level accountability outcomes of public schools in Chicago, find that the effect of crime exposure dies out beyond 0.3 miles.[10] We present our baseline model as follows:

$$TS_{ist} = \sum_{d \in \{0.1,0.2,0.3\}} (Crime_{sdwt}\delta_{1d} + Crime_{sdwt}Female_i\delta_{2d}) + X_{it}\beta + \alpha_s + \gamma_t + u_{ist} \quad (1)$$

where TS_{ist} is the normalized test score of student i in school s in year t; $Crime_{dswt}$ is an indicator of whether school s had at least one violent crime within distance d of school s during w weeks before the test date in year t; d=0.1 miles indicates the violent crimes occurring within 0.1 miles of a school, and d=0.2 miles (d=0.3 miles) excludes violent crimes occurring up to 0.1 miles (0.2 miles), hence d avoids double-counting; $Female_i$ is an indicator of whether student i is female; X_{ist} are time-varying student controls; α_s are school fixed effects; γ_t are year fixed effects; and u_{ist} is an error term.

This specification allows us to control for observed and unobserved characteristics of the schools that are constant over time as well as for citywide trends in student performance. The coefficients of interest are δ_{1d} and δ_{2d}. The former can be interpreted as the average effect of being exposed to violent crime at a distanceon test scores for male students and the latter as the differential effect on females, as compared to males. That is, the average effect of being exposed to violent crime for female students is given by $\delta_{1d} + \delta_{2d}$ and the gender gap

[10] We have also considered different distances including 0.15 miles, 0.25 miles, 0.5 miles, and even up 1.0 miles and find that, similar to Casey, Schiman, and Wachala (2018), our treatment effect is highly local — the effect for violent crimes occurring beyond 0.2 miles is not statistically significant.

effect is directly captured by δ_{2d}. We additionally control for school municipality-by-year fixed effects, where we identify δ_{1d} and δ_{2d} by comparing student test scores in exposed and non-exposed schools in the same municipality. Time-varying student controls include 8th grade cumulative GPA fixed effects, 8th grade math GPA fixed effects, parents' education fixed effects, the number of books and personal computers at home fixed effects, and an indicator variable for students' gender. Standard errors are clustered at the school level to allow errors to be correlated within schools over time.

Our research design relies on two identifying assumptions: First, students in schools that were exposed to violent crime would have experienced changes in test scores similar to those in non-exposed schools in the absence of crime. Second, the composition of students in exposed and non-exposed schools did not change systematically over time. We provide a set of graphical and regression-based evidence to support the plausibility of these assumptions in our setting, along with evidence on the robustness of our results. First, we include school-specific linear time trends to relax the assumption that school-level unobservable characteristics are constant during the period we analyze. We also include municipality of residence-by-year fixed effects to control for unobserved heterogeneity in the municipalities where students reside. Second, we show the null effects on test scores of being exposed to violent crime *after* the test. Finally, we find no evidence that the composition of students changed following the occurrence of violent crimes in close proximity of schools.

5 Results

5.1 Main Results

Table 1 shows the estimated effects of violent crime exposure the week before the exam on high-stakes standardized test scores based on the difference-in-differences model represented by Equation (1). Column 1 shows the baseline specification which includes a female indicator, school fixed effects, and year fixed effects. In Column 2, we additionally control for parental education by including mother's and father's education level fixed effects. In Column 3, we also control for students' academic ability by including previous grade cumulative GPA and math GPA fixed effects. In Column 4, we also control for other time-varying determinants of student performance by including the number of books and personal computers at home fixed effects. In Column 5, we also add school-specific linear time trends. In Column 6, we further control for school municipality-by-year fixed effects. In Column 7, we present our preferred specification that additionally controls for municipality of residence-by-year fixed effects.

Regardless of the specification, the estimated effects in Table 1 indicate that students' exposure to violent crime occurring within 0.1 miles radius of a middle school one week before the test decreases female students' high-stakes standardized test scores but not males', creating a significant gender gap in performance and that the effect vanishes as the distance between schools and the location of violent crimes increases.

The estimated effects from our preferred specification in Column 7 show findings in three-fold. First, male students' test scores are not affected by exposure to violent crimes during the week prior to the test, compared to non-exposed male students. Second, female students' test scores decrease by approximately 11 percent of a standard deviation after the crime exposure, compared to non-exposed females. This asymmetric adverse effect potentially caused by differential psychological responses by gender creates a significant gender gap in test scores which is explicitly measured by $\delta_{2,0.1mile}$. It shows that the gap in test scores between female and male students who are exposed to violent crimes the week before the COMIPEMS exam is 10.9 percent of a standard deviation larger than the gender gap of those non-exposed to such environment.[11] Third, the point estimates for violent crimes occurring within 0.2 and 0.3 miles around schools are not statistically significant.[12] Importantly, the fact that the difference-in-differences estimates in Table 1 are robust to different specifications suggests that the variation of violent crime exposure over time is *as good as random*.

To further investigate whether the effects are transitory, we explore different timings of exposure to violent crimes with respect to test dates. Using our preferred specification, we gradually increase the time window of exposure up to four weeks before the test. The results in Table 2 show that the effect on female students' test scores is transitory, suggesting a temporary mental distress induced by crime exposure. This result is consistent with Dustmann and Fasani (2015), who find a negative temporary impact of violent crime exposure on females' mental well-being but not on males'. Their study highlights that the effect being

[11] In Table B.1, we show that students' exposure to violent crime during one week before the test does not affect the probability of not taking the exam.

[12] Our finding is in line with previous literature on the effects of exposure to violence on education outcomes. Casey, Schiman, and Wachala (2018) find that the effect is strongest for violent crimes occurring within 0.1 miles and that the effect dies out beyond 0.3 miles. Monteiro and Rocha (2017) find that the effect of being exposed to drug-related violence dies beyond 250 meters (0.16 miles).

temporary cannot be neglected due to the repeated nature of crime exposure. A similar argument holds in our context as such a temporary shock can have both short-term and long-term consequences for human capital development as the test scores have predictive power of future education quality.

To better understand how crime exposure affects the high school placement outcome of those female students exposed to violent crime, we exploit information on students' priority list of high schools and their cutoff scores at any given year, along with students' actual placement. We define misplacement as students being placed at high schools that are lower ranked on their priority list than the schools they would have otherwise been assigned to if they were not exposed to violent crime. More specifically, given the actual test scores, we use the estimates from our preferred specification in Table 1 Column 7 to construct the counterfactual scores and compare the actual and the counterfactual score with the cutoffs of schools on their priority list. A back-of-the-envelope calculation indicates that, of the 1,295 female students who were exposed to violent crimes occurring within 0.1 miles from their schools during the week before the test, approximately 19 percent are misplaced due to crime exposure.

Estrada and Gignoux (2017) show that admission to elite high schools in Mexico City results in access to better education quality: smaller class sizes, less students per computer, and more college educated teachers. In addition, Dustan, De Janvry, and Sadoulet (2017) find that attending an elite high school in the Mexico City Metropolitan Area increases future academic performance in low-stakes tests but it also increases the probability of dropping out. They argue that elite schools might be too demanding for students in the lower tail of the COMIPEMS test score distribution in their schools.

5.2 Robustness Checks

To provide evidence of the robustness of our results on the gender gap in the test score, we conduct an event study analysis that employs a modified version of our preferred specification. As Figure 3 shows, instead of gradually increasing the time window inclusively, this model allows for differences in the gender gap for each of the following periods: five or more weeks prior to the test (indicated by -5 in the figures), four weeks to one week before, the weekend of the test, one to four weeks after the test, and five or more weeks after the test (indicated by 5 in the figures). All estimates are relative to the reference group who are exposed to violent crime occurring within 0.1 miles during five or more weeks after the exam. These estimates, although less precise, are consistent with our regression analysis from Table 2; crime exposure before the COMIPEMS exam widens the performance gap between female and male students and the effect is not persistent. Also, the effect vanishes beyond 0.1 miles of school neighborhoods. More importantly, these estimates lend support to our identification strategy as the estimated gender gap effects of being exposed to violent crime one to four weeks *after* the exam are close to zero and statistically insignificant. In other words, our results do not seem to be driven by a spurious correlation between test scores and violent crime exposure.

To provide further evidence on the distance between schools and violent crimes, we conduct an event study analysis by distance with increments of 0.05 miles. Figure 4 indicates that the magnitude of the effect becomes smaller as the distance increases and the effect vanishes beyond 0.1 miles.

We note that after controlling for students' characteristics in Table 1, we missed roughly 15 percent of students in our sample.[13] Non-random sample attrition could be a threat to identification if missing students are systematically enrolled in schools that were exposed to violent crimes the weeks *prior* to the exam or if female students were more likely to leave the sample. To consider this possibility, in Table B.2, we test for non-random attrition of students to further provide supportive evidence on the validity of our identification strategy. We estimate the effects of crime exposure during the weeks before the COMIPEMS exam on an indicator variable of having missing values on at least one of the individual characteristics included in our preferred specification. The results show that exposure to violent crime does not affect the probability of attrition, with point estimates in all columns very close to zero and statistically insignificant. These results highlight the fact that attrition is not correlated with changes in exposure to violent crimes.

It is also possible that students enrolled in schools that were exposed to violent crimes during the weeks around the exam are systematically different from those enrolled in schools that were non-exposed. As a result, the effects we estimate might instead represent these systematic differences. To account for the potential differences, we use an alternative source of variation where we restrict our sample to schools that were ever exposed to violent crimes

[13] These missing students did not answer all questions in the socio-demographic questionnaire when they submitted their application. They have missing information on at least one of the following characteristics: father's education, mother's education, the number of books at home, the number of personal computers at home, cumulative GPA at eighth grade, or math GPA at eighth grade.

within 0.3 miles either during the 4 weeks *before* or 4 weeks *after* the test. Doing so enables us to examine whether our estimates are driven by systematic differences between students in schools that were ever exposed to violent crimes within 0.3 miles and students in schools that were non-exposed to violent crime within the same distance. The results in Table B.3 are very similar in magnitude and statistical significance to our main results reported in Table 2, reassuring that our estimates are not driven by the systematic differences across exposed and non-exposed students.[14]

While we observe the same schools over the period of 2013 to 2016, students in these schools at any given time could have different characteristics. This is a concern if the difference in students' traits is related to treatment. It is difficult to imagine that the timing of violent crime occurring nearby a school relative to exam dates is endogenous. That is, the local violent crimes occurring within a close distance of schools during the week before the exam dates is a result of changing characteristics of students or the composition of students enrolled in affected schools. Even if the timing of the local violent crimes is exogenous to characteristics of students enrolled in a school, we consider selection in enrollment to schools with and without a record of local violent crimes in a short distance. Although it is highly unlikely that parents of low performing students selectively enroll their children in a school that experienced local violent crimes in close distance, parents of high performing students might selectively enroll their children in a school without any local violent crimes. Thus, we perform a set of balancing tests by estimating the effect of exposure to violent crimes

[14] We present the event study analysis for this restricted sample in Figure A.3, and it is almost identical to the one in Figure 3.

on each of the observed individual characteristics using our preferred specification. That is, we examine whether traits of students enrolled in schools change as a result of local violent crimes occurring within certain distances from schools. In tables B.4 - B.6, we find no evidence that the characteristics of students enrolled in schools are changing following the occurrence of local violent crime. This evidence gives us confidence that our estimates are not driven by systematic changes on students' characteristics in treated schools.

5.3 Other-Violent Crimes and Non-Violent Crimes

Using other types of crimes, we further provide evidence on the mechanisms driving the effects of violent crime exposure on the gender gap in test scores. First, we categorize various types of robbery and forcible rape as other-violent crimes and estimate the effect of other-violent crimes on test scores. Our prior is that the estimates are noisier for this analysis due to measurement error induced by under-reporting that is tied to these particular types of crimes. Table 3 shows that, on average, the gender gap in test scores is not affected by other-violent crimes, with a few negligible exceptions. The results indicate that mental distress caused by other-violent crimes has almost no meaningful impact on cognitive performance on the test to the degree that it does not exacerbate the gender performance gap.

Second, we define various types of larceny that do not involve violence as non-violent crimes and examine whether these crimes have any impact on test scores. Non-violent crimes, compared to violent crimes (homicide and firearm injuries), are deemed much less salient so that students are less likely to be aware of such crime events. Even if students are aware of such crime incidents, non-violent crimes may generate little to no fear in the nearby community. Thus, we expect these crimes to have no significant impact on test scores. In Table 4, we show that, on average, exposure to non-violent crimes has no statistically meaningful impact on test scores. The estimates suggest that regardless of the distance and the timing of the crime exposure with respect to test dates, non-violent crime exposure does not affect students' cognitive performance on the test. This finding is supported by Cornaglia, Feldman, and Leigh (2014), who show that property crime rates do not affect mental well-being, whereas violent crime rates have a significant adverse impact. These results also suggests that our estimated effects for violent crimes reported in Table 2 are not driven by spurious correlation between test scores and crimes in general.

5.4 Heterogeneity

In this section, we explore heterogeneity in the treatment effects as particular subgroups of students can be more responsive to violent crime exposure. In particular, we consider heterogeneous effects by poverty level, crime rates of school neighborhoods, and across the test score distribution.

We first examine our results by poverty level of school neighborhoods using the 2010 urban poverty index of the AGEB where the school is located by dividing our sample into two groups. In Table 5, *low poverty* (*high poverty*) indicate school neighborhoods with a poverty index below (above) the median. The results present several important findings. First, despite the difference in economic resources across the poverty groups, male students' test scores are not adversely affected by crime exposure. The gender gap is 10.3 and 11.6 percent of a standard deviation in *low* and *high poverty* schools, respectively, but they are not statistically different from each other. Finally, the effect on female students in *high poverty* schools, compared to other female students who are in the same poverty group but are unexposed to such crimes, is statistically significant for the exposure to violent crimes occurring two weeks prior to the test (p-value=0.03), suggesting that the crime-induced mental distress lasts longer for this group of females.[15]

Students that are continuously exposed to violent crime may adapt to their environment and become desensitized to such events. Hence, we examine how students' responses vary by crime rates at the AGEB (census area) level. We do so by computing per capita crime rates for each census area,[16] and then splitting the sample into two groups in the same manner as with poverty level. In Table 6, *low crime* (below median crime rates) indicates school neighborhoods that are relatively safe. We find that male students' test scores are not affected by violent crimes regardless of the differential surrounding safety levels. Similar to our results by poverty, the effect is close to zero and statistically insignificant.

Unlike our findings of no difference in the gender gap across poverty groups (10.3%SD versus 11.6%SD; both statistically significant), the difference in the gender gap point estimates across the two crime groups is noticeable but they are not statistically different for one another. For the *low crime* group, the gender gap in test scores is substantially widened by 12.4 percent of a standard deviation after being exposed to violent crimes occurring within

[15] For female students in *low poverty* schools, the effect of exposure to violent crimes occurring two weeks before the COMIPEMS exam is close to zero (-0.023%SD) and statistically insignificant (p-value=0.54).

[16] We divide the total number of all types of crimes occurred from January 1st, 2013 to May 31st, 2013 by the population at each census area as a proxy for pre-trends in crime.

0.1 miles during the week before the test. Also, the effect of exposure during the two weeks prior to the test is less significant but non-negligible. The results suggest that employing a high-stakes entrance exam underestimates academic abilities of female students who are attending schools in relatively safe areas.[17]

We now turn to the heterogeneous treatment effect by subjects using the two groups of subjects described in Section 3. While it is reasonable to hypothesize that violent crime exposure affects one of these groups more adversely through possible different channels such as prompt critical thinking and retrieval, it is certainly possible to have an indistinguishable impact if crime exposure affects them equally or if it disturbs overall preparation for the test. The results in Table 7 show that the average gender gap effects on math and sciences and verbal and humanities scores are not meaningfully different from one another.

We then examine the effects of violent crime exposure at different points of the test score distribution by using unconditional quantile regressions described in Firpo, Fortin, and Lemieux (2009), and our preferred specification. Figure 5 Panel (a) presents the unconditional quantile estimates on total score. To further disentangle the distributional effects by subjects, panels (b) and (c) shows the effects on math and sciences and verbal and humanities, respectively. The estimates in all three panels show that exposure to violent crime occurring within 0.1 miles one week before the test widens the gender performance gap at all points in the total score distribution, although the point estimates from 60 percentile to 90 percentiles are less precise. In panels (b) and (c), we observe a slightly different pattern

[17] We provide additional evidence that our results by poverty level and crime rates are robust even after altering our control group through restricting our samples in the same manner as for our main analysis. In tables B.7 and B.8, we explore the heterogeneity using our restricted sample, the results are very similar to the results reported in tables 5 and 6.

of the distributional effects. The average gender gap effect on math and sciences scores, indicated by a solid line, is largely driven by students who perform around the median, in the range of 30 - 60 percentile, and the adverse effect is the largest in the range of 40 - 50 percentile. On the other hand, the average gender gap effect on verbal and humanities scores is mainly driven by students who perform below the median, in the range of 10 - 40 percentile, and the effect is largest in the range of 20 - 30 percentile.

6 Conclusions

This study shows empirical evidence that the use of high-stakes test scores as a unique sorting mechanism for high school placement results in a gender-biased allocation of students to high schools due to exposure to violent crime.

By exploiting the geographic coordinates of schools and crimes in the context of Mexico City's centralized high school admission system, we offer several important results. First, male students' test scores are not affected by exposure to violent crimes, regardless of the distances between schools and crimes and the timings of exposure relative to the exam dates. The socioeconomic status and crime level of school neighborhoods are irrelevant to male test-takers' cognitive performance on the entrance exam. Second, female students' test scores decrease after crime exposure, creating a significant gender gap in performance. The effect is highly localized both in time and geographic proximity, suggesting that temporary psychological harm is one of the main mechanisms through which exposure to violent crime affects cognitive performance.

Among females, those attending schools in relatively economically disadvantaged neighborhoods experience the impact of violent crime exposure for a longer period. Their test scores drop by more than 11 and 8 percent of a standard deviation after being exposed to violent crime within 0.1 miles from their schools one and two weeks before the test, respectively, compared to similar female students who are not exposed to such incidents. Furthermore, females attending schools in relatively safe neighborhoods seem more responsive to violent crimes. Lastly, the adverse effect on females' test scores leads to a gender-biased allocation of human capital. A back-of-the-envelope calculation based on our main results suggests that approximately 19 percent of female students exposed to violent crime are assigned to less-preferred high schools than the ones to which they would have otherwise been assigned in the absence of violent crime.

Our results indicate that when used as the sole measure of academic ability, high-stakes entrance exams exacerbate gender inequality in education, since only female students are adversely affected by local violent crimes. The results also suggest that the exam worsens the disparity among females as more economically burdened female students experience for a longer period of time the impact of exposure to violent crimes on test scores. Moreover, the null effects on male students and on females attending schools in high crime areas suggest that adolescents who are repeatedly exposed to violent crimes are desensitized to such crimes.

We provide both graphical and regression based evidence that our results are robust. However, we are unable to provide direct empirical evidence, in our setting, on the mechanisms driving the effects on test scores. While we have detailed survey information about students' mental health (e.g., depression, anxiety, aggressiveness, and concentration problem), the difficulty is in identifying the exact timing in which students filled the context questionnaire, making it difficult to establish causality. Disentangling the potential mechanisms and providing evidence on the long-term economic consequences of exposure to violent crimes are important areas for future research.

References

Azmat, G., C. Calsamiglia, and N. Iriberri (2016): “Gender differences in response to big stakes,” *Journal of the European Economic Association*, 14, 1372–1400.

Barrera, F. and A. M. Ibánez (2004): “Does violence reduce investment in education?: A theoretical and empirical approach,” Technical report, Universidad de los Andes-CEDE.

Becker, G. S. and Y. Rubinstein (2011): “Fear and the response to terrorism: An economic analysis,” *CEP Discussion Paper No 1079*.

Bobba, M. and V. Frisancho (2014): “Learning about oneself: The effects of signaling academic ability on school choice,” *Unpublished working paper*.

Brown, R. and A. Velásquez (2017): “The effect of violent crime on the human capital accumulation of young adults,” *Journal of Development Economics*, 127, 1–12.

Burdick-Will, J. (2013): “School violent crime and academic achievement in Chicago,” *Sociology of Education*, 86, 343–361.

Burdick-Will, J. (2016): “Neighborhood violent crime and academic growth in Chicago: lasting effects of early exposure,” *Social Forces*, 95, 133–158.

Cai, X., Y. Lu, J. Pan, and S. Zhong (2019): “Gender gap under pressure: Evidence from China’s national college entrance examination,” *Review of Economics and Statistics*, 101, 249–263.

Carrell, S. E., M. Hoekstra, and E. Kuka (2018): "The long-run effects of disruptive peers," *American Economic Review*, 108, 3377–3415.

Casey, M., J. C. Schiman, and M. Wachala (2018): "Local violence, academic performance, and school accountability," *AEA Papers and Proceedings*, 108, 213–216.

Caudillo, M. L. and F. Torche (2014): "Exposure to local homicides and early educational achievement in Mexico," *Sociology of Education*, 87, 89–105.

Cho, H. (2017): "The effects of summer heat on academic achievement: A cohort analysis," *Journal of Environmental Economics and Management*, 83, 185–196.

Cornaglia, F., N. E. Feldman, and A. Leigh (2014): "Crime and mental well-being," *Journal of Human Resources*, 49, 110–140.

Dell, M. (2015): "Trafficking networks and the mexican drug war," *American Economic Review*, 105, 1738–79.

Dustan, A., A. De Janvry, and E. Sadoulet (2017): "Flourish or fail? The risky reward of elite high school admission in Mexico City," *Journal of Human Resources*, 52, 756–799.

Dustmann, C. and F. Fasani (2015): "The effect of local area crime on mental health," *The Economic Journal*, 126, 978–1017.

Ebenstein, A., V. Lavy, and S. Roth (2016): "The long-run economic consequences of high-stakes examinations: Evidence from transitory variation in pollution," *American Economic Journal: Applied Economics*, 8, 36–65.

Estrada, R. and J. Gignoux (2017): "Benefits to elite schools and the expected returns to education: Evidence from Mexico City," *European Economic Review*, 95, 168–194.

Firpo, S., N. M. Fortin, and T. Lemieux (2009): "Unconditional quantile regressions," *Econometrica*, 77, 953–973.

Graff Zivin, J., Y. Song, Q. Tang, and P. Zhang (2018): "Temperature and high-stakes cognitive performance: Evidence from the national college entrance examination in China," Technical report, National Bureau of Economic Research.

Heissel, J. A., E. K. Adam, J. L. Doleac, D. N. Figlio, and J. Meer (2018): "Testing, stress, and performance: How students respond physiologically to high-stakes testing," Technical report, National Bureau of Economic Research.

Monteiro, J. and R. Rocha (2017): "Drug battles and school achievement: evidence from rio de janeiro's favelas," *Review of Economics and Statistics*, 99, 213–228.

Park, J. (2018): "Hot temperature, high stakes exams, and avoidance behavior: Evidence from New York City public schools," *Unpublished Manuscript, Harvard University Economics Department, Submitted.*

Rodriguez, C. and F. Sanchez (2012): "Armed conflict exposure, human capital investments, and child labor: Evidence from Colombia," *Defence and Peace Economics*, 23, 161–184.

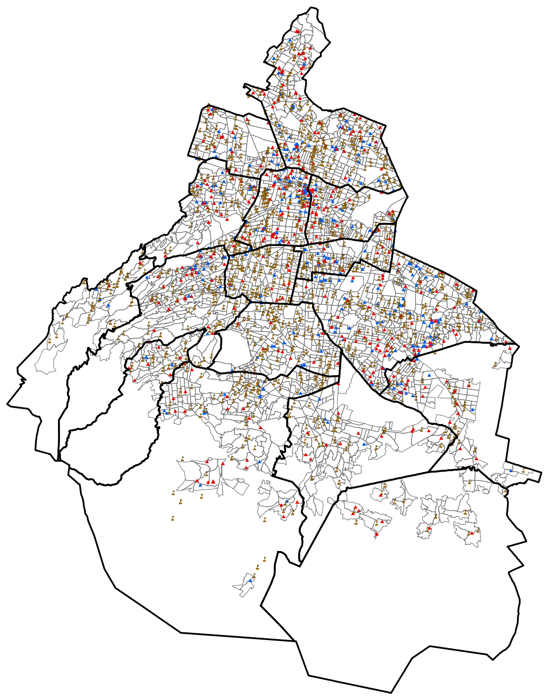
Sharkey, P. (2010): "The acute effect of local homicides on children's cognitive performance," *Proceedings of the National Academy of Sciences*, 107, 11733–11738.

Sharkey, P., A. E. Schwartz, I. G. Ellen, and J. Lacoe (2014): "High stakes in the classroom, high stakes on the street: The effects of community violence on student's standardized test performance," *Sociological Science*, 1, 199.

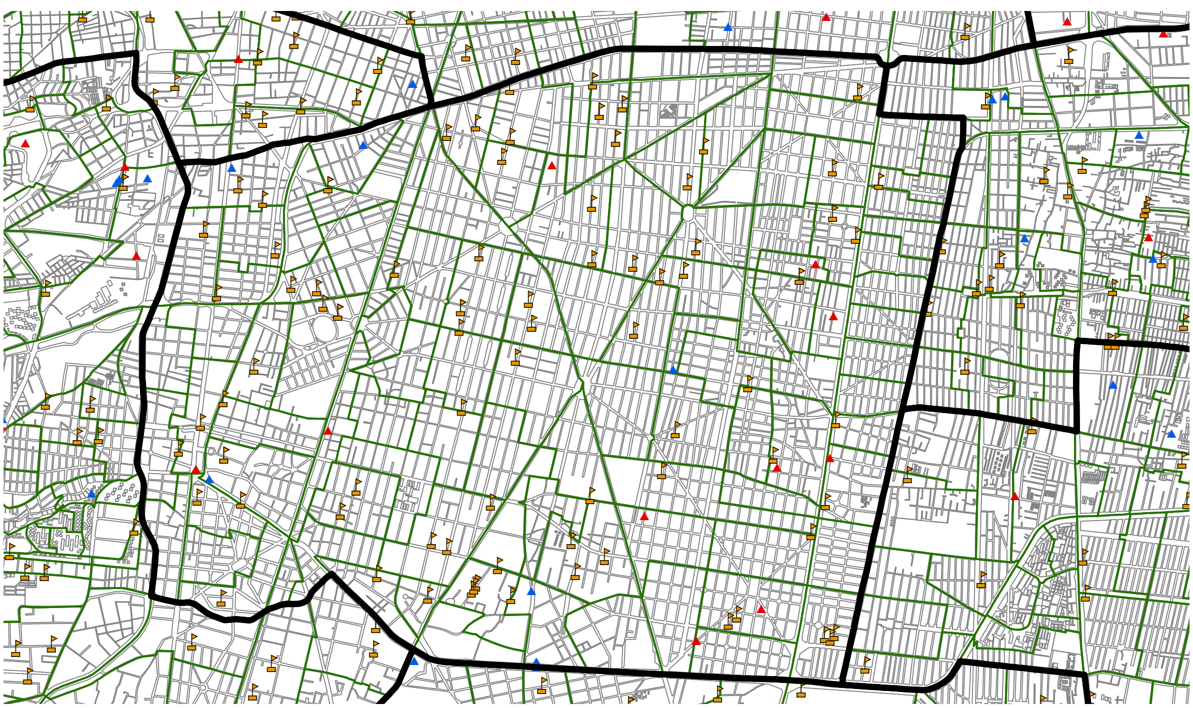
Velásquez, A. (2019): "The economic burden of crime: Evidence from Mexico," *Journal of Human Resources*, 0716–8072r2.

Figure 1: Middle Schools and Violent Crimes within 4 Weeks Before the COMIPEMS Test 2013–2016

(a) All municipalities

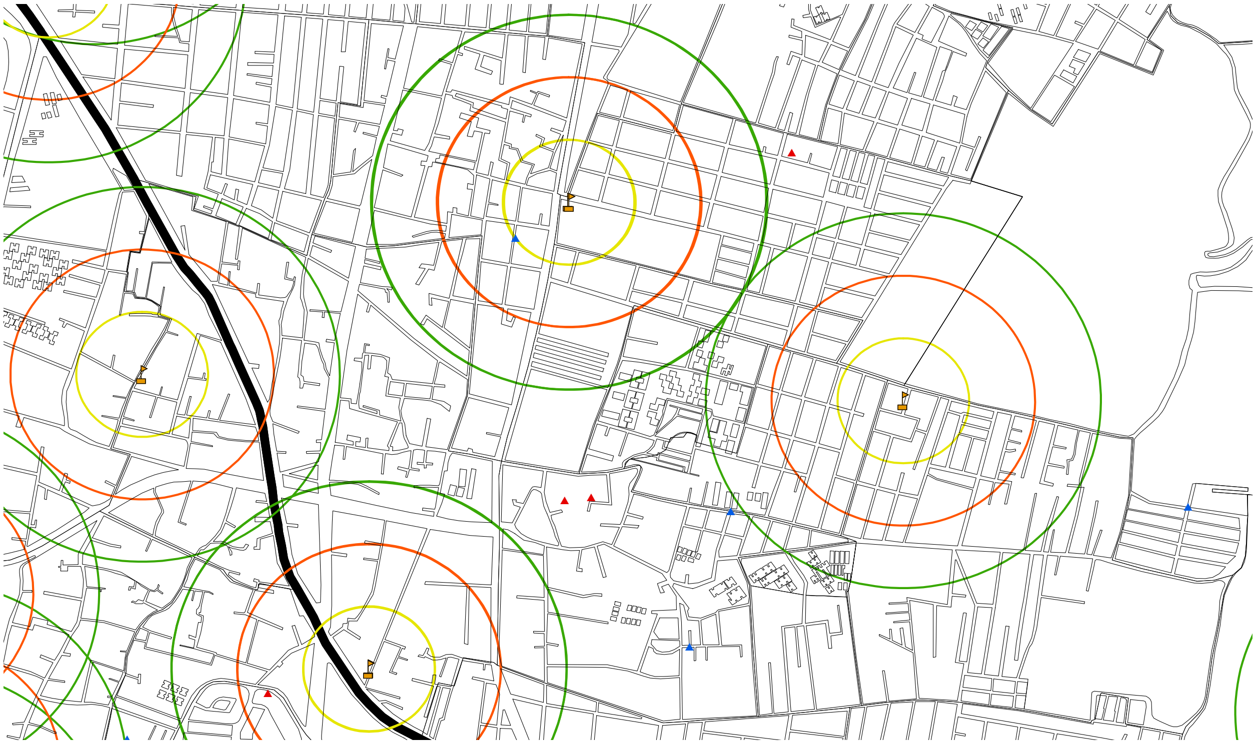


(b) A close-up of a particular municipality



Notes: Each panel shows the geographic distribution of middle-schools (yellow flags), homicides (red triangles), and firearm injuries (blue triangles) that occurred within 4 weeks before each year's COMIPEMS exam for the period of 2013 to 2016. Panel (a) shows a total of 830 violent crimes for the time frame we analyzed. The bold black line represents a municipality border. Panel (b) shows a close-up to a municipality.

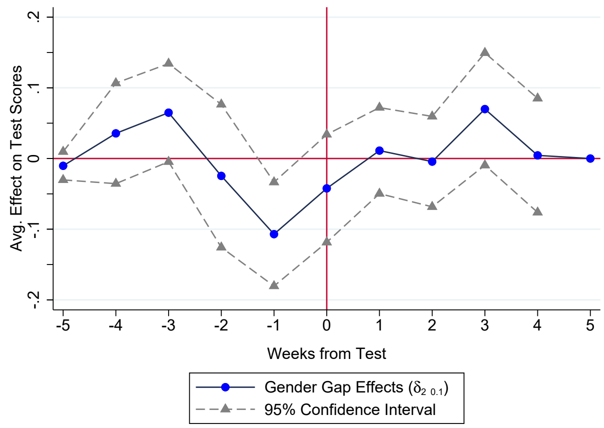
Figure 2: Buffer Analysis for Violent Crimes within 4 Weeks Before the COMIPEMS Test 2013-2016



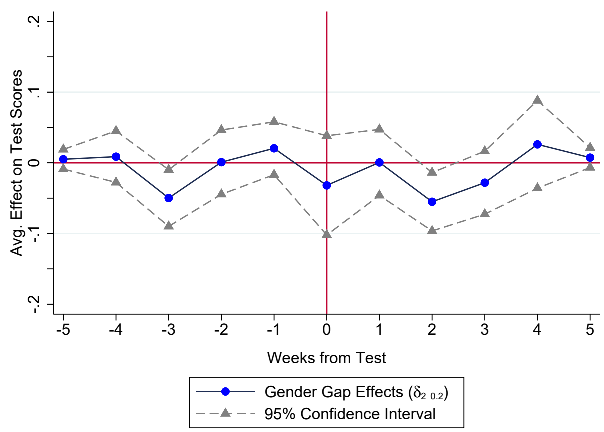
Notes: This figure shows buffers of 0.1, 0.2, and 0.3 miles around schools, homicides, and firearm injuries that occurred within 4 weeks before the COMIPEMS exam from 2013 to 2016. The bold black line represents a municipality border and the gray lines represent census block.

Figure 3: Event Study by Weeks of the Effect of Exposure to Violent Crime on the Gender Gap

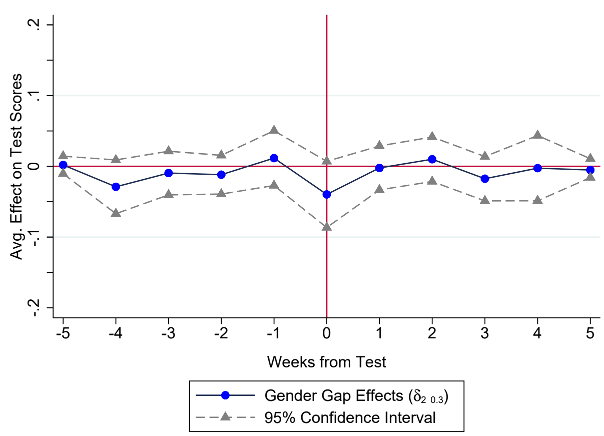
(a) 0.1 Miles



(b) 0.2 Miles

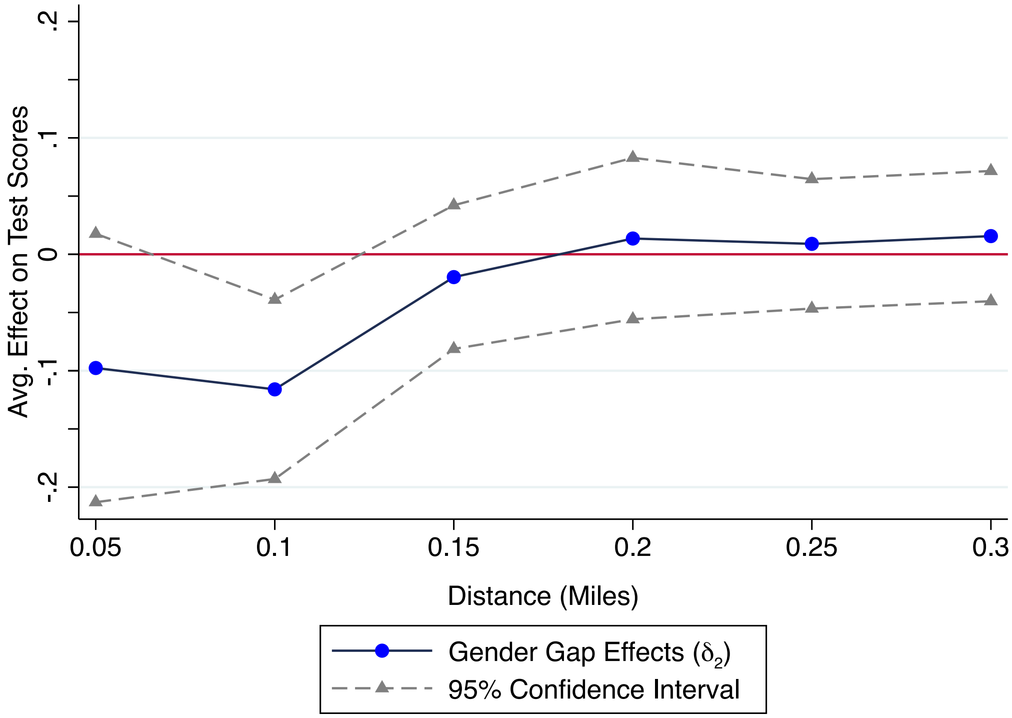


(c) 0.3 Miles



Notes: Each panel shows the event study estimates by weeks, for each distance-ring, of the gender gap effect of exposure to violent crime around the school *before*, *during*, and *after* the COMIPEMS test date, relative to the difference of being exposed to crime during 5 or more weeks *after* the COMIPEMS test. All estimates are from a single regression.

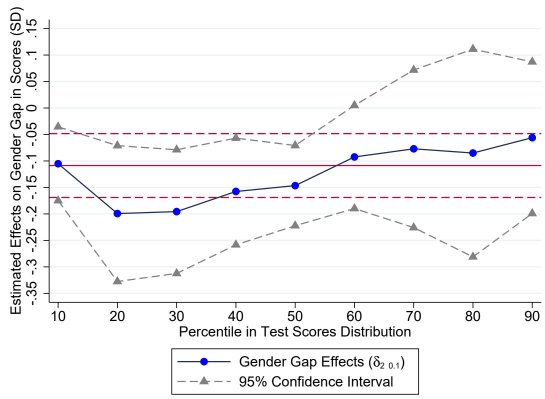
Figure 4: Event Study By Distance of the Effect of Exposure to Violent Crime on the Gender Gap



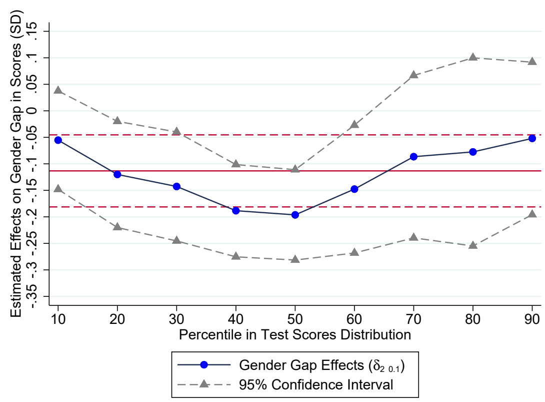
Notes: This figure shows the event study estimates of the gender gap effect of exposure to violent crime for each distance from 0.05 miles to 0.3 miles. All estimates are from a single regression.

Figure 5: Estimated Effects on Percentiles in Test Scores Distribution

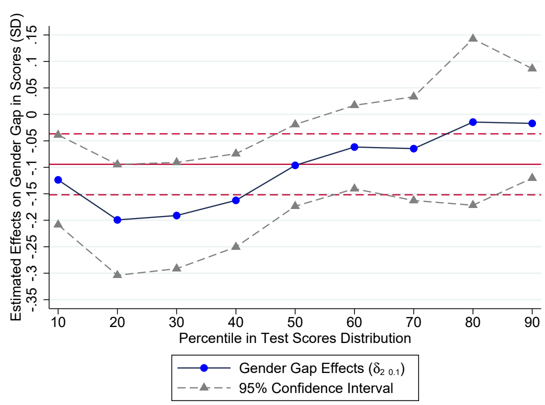
(a) All Subjects



(b) *Math & Sciences*



(c) *Verbal & Humanities*



Notes: Each panel shows the Unconditional Quantile Regression (Firpo, Fortin, and Lemieux, 2009) estimates on the gender gap in test scores using the preferred specification for the overall score and by subject. The horizontal solid line in panel (a) represents the average effect from Table 2 Column (1); the horizontal solid line in (b) and (c) represents the average effect from Table 7 columns (1) and (5), respectively; the horizontal dash lines represent their 95% confidence intervals. Math & Sciences includes math, math ability (reasoning), physics, chemistry, and biology; and Verbal & Humanities includes verbal ability(reasoning), Spanish, history, geography, and civics and ethics.

Table 1: Estimated Effects on Test Scores of Violent Crimes One Week Before the Test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	0.038	0.052	0.010	0.003	-0.008	-0.007	-0.007
	(0.040)	(0.043)	(0.031)	(0.030)	(0.029)	(0.031)	(0.031)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	-0.125***	-0.146***	-0.111***	-0.106***	-0.106***	-0.108***	-0.109***
	(0.035)	(0.040)	(0.033)	(0.032)	(0.032)	(0.031)	(0.031)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	-0.014	-0.020	-0.005	-0.001	0.017	0.019	0.020
	(0.027)	(0.031)	(0.030)	(0.027)	(0.031)	(0.029)	(0.029)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	0.028	0.028	0.010	0.012	0.011	0.010	0.011
	(0.025)	(0.027)	(0.022)	(0.020)	(0.020)	(0.020)	(0.020)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	-0.011	-0.013	-0.017	-0.019	0.002	0.014	0.014
	(0.017)	(0.019)	(0.020)	(0.021)	(0.019)	(0.019)	(0.019)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	-0.011	-0.007	0.010	0.009	0.007	0.007	0.007
	(0.024)	(0.023)	(0.021)	(0.022)	(0.022)	(0.021)	(0.022)
N	399025	354571	341935	340105	340105	340105	340105
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.026	0.003	0.000	0.000	0.001	0.001	0.001
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.628	0.768	0.823	0.653	0.309	0.251	0.234
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}} = 0$)	0.197	0.249	0.696	0.592	0.592	0.250	0.245
Individual controls (Parental Education)	N	Y	Y	Y	Y	Y	Y
Individual controls (Academic Ability)	N	N	Y	Y	Y	Y	Y
Individual controls (Other Characteristics)	N	N	N	Y	Y	Y	Y
School-specific time trends	N	N	N	N	Y	Y	Y
School municipality-by-year FE	N	N	N	N	N	Y	Y
Residence municipality-by-year FE	N	N	N	N	N	N	Y

Notes: All specifications include school fixed effects, year fixed effects, and a female indicator. Individual controls include academic ability (8th grade general GPA and math GPA fixed effects), parental education (mother's education and father's education fixed effects), and other characteristics (the number of books and the number of personal computers at home fixed effects). Violent crimes include homicides and firearm injuries. Standard errors in parentheses are clustered at the school level. *, **, *** significant at the 10%, 5%, and 1% level, respectively.

Table 2: Estimated Effects of Violent Crimes on Test Scores by Weeks Before the Test

	1 week (1)	2 weeks (2)	3 weeks (3)	4 weeks (4)
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	-0.007	0.009	-0.007	0.001
	(0.031)	(0.024)	(0.021)	(0.020)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	-0.109***	-0.064**	-0.028	-0.005
	(0.031)	(0.032)	(0.030)	(0.025)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	0.020	0.007	0.011	-0.002
	(0.029)	(0.020)	(0.015)	(0.013)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	0.011	0.005	-0.015	-0.008
	(0.020)	(0.016)	(0.013)	(0.012)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	0.014	0.001	0.006	0.006
	(0.019)	(0.015)	(0.012)	(0.011)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	0.007	0.000	0.001	-0.004
	(0.022)	(0.013)	(0.010)	(0.009)
N	340105	340105	340105	340105
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.001	0.048	0.126	0.834
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.234	0.522	0.786	0.462
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}} = 0$)	0.245	0.936	0.580	0.857

Notes: All specifications include school fixed effects, year fixed effects, a female indicator, individual controls, school-specific time trends, school municipality-by-year fixed effects, and residence municipality-by-year fixed effects. Individual controls include academic ability (8th grade general GPA and math GPA fixed effects), parental education (mother's education and father's education fixed effects), and other characteristics (the number of books and the number of personal computers at home fixed effects). Violent crimes include homicides and firearm injuries. Standard errors in parentheses are clustered at the school level. *, **, *** significant at the 10%, 5%, and 1% level, respectively.

Table 3: Estimated Effects of Other-Violent Crimes on Test Scores by Weeks Before the Test

	1 week (1)	2 weeks (2)	3 weeks (3)	4 weeks (4)
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	-0.018	-0.014	-0.010	-0.013
	(0.014)	(0.010)	(0.009)	(0.008)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	-0.006	0.006	0.003	0.013*
	(0.013)	(0.009)	(0.008)	(0.007)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	0.005	0.001	0.001	0.002
	(0.008)	(0.007)	(0.007)	(0.006)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	-0.015*	-0.006	-0.011*	-0.006
	(0.008)	(0.006)	(0.006)	(0.006)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	-0.013*	-0.006	-0.009	-0.009
	(0.008)	(0.006)	(0.006)	(0.007)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	-0.005	-0.009*	-0.004	-0.003
	(0.007)	(0.006)	(0.006)	(0.006)
N	340105	340105	340105	340105
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.062	0.415	0.395	0.989
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.180	0.492	0.109	0.546
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}} = 0$)	0.015	0.010	0.029	0.070

Notes: All specifications include school fixed effects, year fixed effects, a female indicator, individual controls, school-specific time trends, school municipality-by-year fixed effects, and residence municipality-by-year fixed effects. Individual controls include academic ability (8th grade general GPA and math GPA fixed effects), parental education (mother's education and father's education fixed effects), and other characteristics (the number of books and the number of personal computers at home fixed effects). Other-violent crimes include various types of robbery and forcible rape. Standard errors in parentheses are clustered at the school level. *, **, *** significant at the 10%, 5%, and 1% level, respectively.

Table 4: Estimated Effects of Non-Violent Crimes on Test Scores by Weeks Before the Test

	1 week (1)	2 weeks (2)	3 weeks (3)	4 weeks (4)
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	-0.008	0.003	0.000	-0.007
	(0.014)	(0.012)	(0.010)	(0.010)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	0.024	0.021	0.012	0.012
	(0.015)	(0.013)	(0.011)	(0.010)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	-0.000	0.009	0.011	0.013*
	(0.011)	(0.009)	(0.008)	(0.008)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	-0.002	-0.001	-0.000	-0.004
	(0.009)	(0.008)	(0.007)	(0.007)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	0.006	0.005	-0.000	0.001
	(0.009)	(0.007)	(0.006)	(0.006)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	-0.006	-0.006	-0.000	-0.005
	(0.008)	(0.006)	(0.006)	(0.006)
N	340105	340105	340105	340105
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.255	0.043	0.242	0.588
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.816	0.347	0.166	0.206
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}} = 0$)	0.966	0.946	0.909	0.501

Notes: All specifications include school fixed effects, year fixed effects, a female indicator, individual controls, school-specific time trends, school municipality-by-year fixed effects, and residence municipality-by-year fixed effects. Individual controls include academic ability (8th grade general GPA and math GPA fixed effects), parental education (mother's education and father's education fixed effects), and other characteristics (the number of books and the number of personal computers at home fixed effects). Non-violent crimes include different types of larceny that do not involve violence. Standard errors in parentheses are clustered at the school level. *, **, *** significant at the 10%, 5%, and 1% level, respectively.

Table 5: Estimated Effects on Test Scores by Weeks Before the Test and Poverty

	Low Poverty				*High Poverty*			
	1 week	2 weeks	3 weeks	4 weeks	1 week	2 weeks	3 weeks	4 weeks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	-0.016	0.035	-0.004	0.001	-0.005	-0.022	-0.016	-0.001
	(0.068)	(0.040)	(0.032)	(0.024)	(0.036)	(0.033)	(0.031)	(0.032)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	-0.103***	-0.058	-0.014	-0.003	-0.116**	-0.067	-0.040	-0.007
	(0.031)	(0.040)	(0.036)	(0.028)	(0.049)	(0.055)	(0.050)	(0.044)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	0.035	0.002	0.020	0.012	0.008	0.014	0.013	-0.002
	(0.027)	(0.028)	(0.021)	(0.017)	(0.044)	(0.029)	(0.023)	(0.019)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	-0.013	-0.008	-0.028	-0.024	0.029	0.012	-0.006	0.004
	(0.035)	(0.023)	(0.019)	(0.017)	(0.022)	(0.021)	(0.018)	(0.017)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	-0.006	-0.023	-0.013	-0.023	0.013	0.010	0.017	0.027*
	(0.031)	(0.020)	(0.016)	(0.015)	(0.027)	(0.021)	(0.016)	(0.014)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	-0.010	-0.003	-0.006	-0.015	0.029	0.009	0.009	0.006
	(0.030)	(0.017)	(0.016)	(0.014)	(0.029)	(0.018)	(0.013)	(0.012)
N	164167	164167	164167	164167	163902	163902	163902	163902
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.148	0.540	0.505	0.928	0.009	0.030	0.120	0.833
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.460	0.830	0.689	0.507	0.302	0.344	0.743	0.911
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}} = 0$)	0.581	0.174	0.233	0.010	0.079	0.271	0.090	0.013

Notes: All specifications include school fixed effects, year fixed effects, a female indicator, individual controls, school-specific time trends, school municipality-by-year fixed effects, and residence municipality-by-year fixed effects. Individual controls include academic ability (8th grade general GPA and math GPA fixed effects), parental education (mother's education and father's education fixed effects), and other characteristics (the number of books and the number of personal computers at home fixed effects). Violent crimes include homicides and firearm injuries. *Low (high) poverty* areas are defined as those below (above) the median census area's poverty index. Standard errors in parentheses are clustered at the school level. *, **, *** significant at the 10%, 5%, and 1% level, respectively.

Table 6: Estimated Effects on Test Scores by Weeks Before the Test and Crime Rate

	Low Crime				*High Crime*			
	1 week	2 weeks	3 weeks	4 weeks	1 week	2 weeks	3 weeks	4 weeks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	-0.020	0.032	0.023	0.036	-0.010	-0.025	-0.031	-0.023
	(0.047)	(0.038)	(0.039)	(0.037)	(0.053)	(0.033)	(0.023)	(0.020)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	-0.124***	-0.081*	-0.061	-0.027	-0.077	-0.042	0.003	0.011
	(0.034)	(0.042)	(0.045)	(0.042)	(0.066)	(0.049)	(0.032)	(0.027)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	-0.067	-0.036	-0.023	-0.020	0.048	0.034	0.030	0.012
	(0.061)	(0.028)	(0.023)	(0.020)	(0.034)	(0.025)	(0.019)	(0.017)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	0.024	0.009	-0.010	-0.011	0.002	0.001	-0.019	-0.005
	(0.023)	(0.019)	(0.019)	(0.017)	(0.027)	(0.022)	(0.018)	(0.017)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	0.002	0.005	0.005	0.015	0.015	-0.010	0.002	-0.005
	(0.033)	(0.023)	(0.017)	(0.016)	(0.024)	(0.018)	(0.015)	(0.014)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	0.016	0.000	0.009	-0.000	0.009	0.006	-0.005	-0.007
	(0.030)	(0.019)	(0.015)	(0.014)	(0.029)	(0.016)	(0.015)	(0.013)
N	161763	161763	161763	161763	159440	159440	159440	159440
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.007	0.216	0.312	0.798	0.175	0.108	0.300	0.649
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.479	0.396	0.202	0.142	0.057	0.110	0.503	0.661
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}} = 0$)	0.486	0.774	0.399	0.357	0.345	0.812	0.851	0.427

Notes: All specifications include school fixed effects, year fixed effects, a female indicator, individual controls, school-specific time trends, school municipality-by-year fixed effects, and residence municipality-by-year fixed effects. Individual controls include academic ability (8th grade general GPA and math GPA fixed effects), parental education (mother's education and father's education fixed effects), and other characteristics (the number of books and the number of personal computers at home fixed effects). Violent crimes include homicides and firearm injuries. *Low (high) crime* areas are defined as those below (above) the median census area's crime rate. Standard errors in parentheses are clustered at the school level. *, **, *** significant at the 10%, 5%, and 1% level, respectively.

Table 7: Estimated Effects on Test Scores by Subjects by Weeks Before the Test

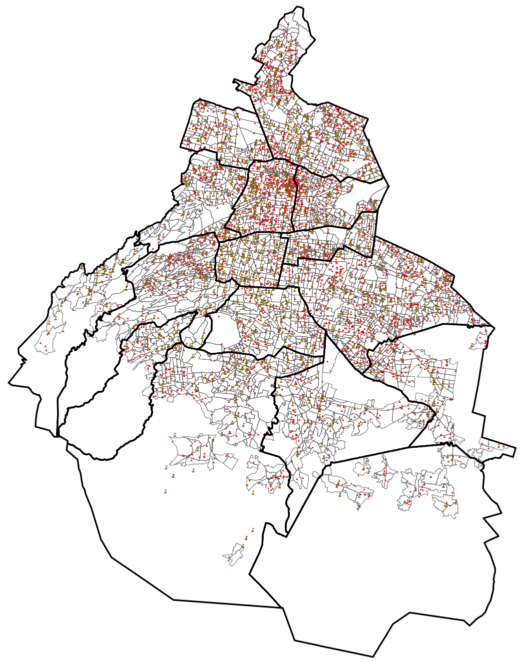
	Math & Sciences				*Verbal & Humanities*			
	1 week	2 weeks	3 weeks	4 weeks	1 week	2 weeks	3 weeks	4 weeks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	-0.006	0.013	-0.004	-0.006	-0.008	0.003	-0.009	0.007
	(0.038)	(0.027)	(0.025)	(0.023)	(0.026)	(0.024)	(0.020)	(0.019)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	-0.113***	-0.064**	-0.026	0.000	-0.094***	-0.059*	-0.026	-0.011
	(0.035)	(0.032)	(0.030)	(0.025)	(0.029)	(0.032)	(0.029)	(0.025)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	0.024	0.004	0.009	0.000	0.013	0.010	0.012	-0.003
	(0.028)	(0.019)	(0.015)	(0.012)	(0.029)	(0.020)	(0.016)	(0.013)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	0.023	0.010	-0.016	-0.011	-0.003	-0.001	-0.013	-0.004
	(0.019)	(0.016)	(0.014)	(0.012)	(0.021)	(0.016)	(0.014)	(0.013)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	0.028	0.009	0.010	0.007	-0.001	-0.007	0.000	0.005
	(0.020)	(0.015)	(0.012)	(0.011)	(0.019)	(0.014)	(0.012)	(0.011)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	0.025	0.007	0.010	0.003	-0.013	-0.008	-0.009	-0.012
	(0.020)	(0.013)	(0.010)	(0.009)	(0.023)	(0.014)	(0.011)	(0.010)
N	340105	340105	340105	340105	340105	340105	340105	340105
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.001	0.070	0.190	0.813	0.005	0.061	0.123	0.866
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.074	0.481	0.679	0.413	0.688	0.623	0.948	0.602
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}}$=0)	0.004	0.244	0.094	0.319	0.463	0.272	0.469	0.484

Notes: *Math & Sciences* includes math, math ability (reasoning), physics, chemistry, and biology; and *Verbal & Humanities* include verbal ability (reasoning), Spanish, history, geography, and civics and ethics. All specifications include school fixed effects, year fixed effects, a female indicator, individual controls, school-specific time trends, school municipality-by-year fixed effects, and residence municipality-by-year fixed effects. Individual controls include academic ability (8th grade general GPA and math GPA fixed effects), parental education (mother's education and father's education fixed effects), and other characteristics (the number of books and the number of personal computers at home fixed effects). Violent crimes include homicides and firearm injuries. Standard errors in parentheses are clustered at the school level. *, **, *** significant at the 10%, 5%, and 1% level, respectively.

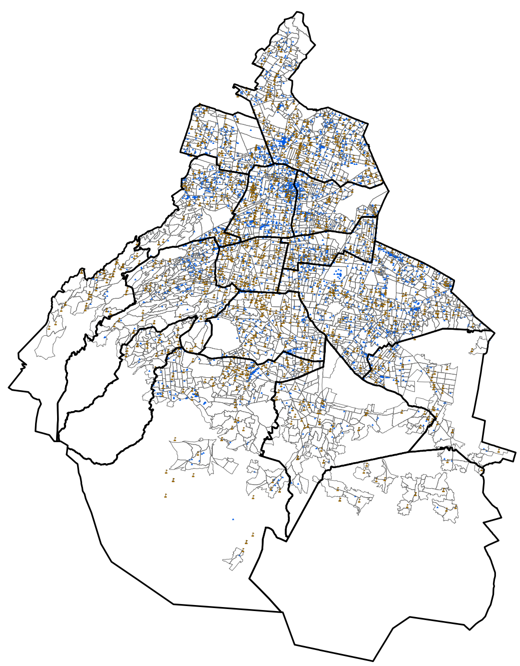
Appendix A Figures

Figure A.1: Violent Crimes and Middle Schools in Mexico City 2013-2016

(a) Middle Schools and Homicides



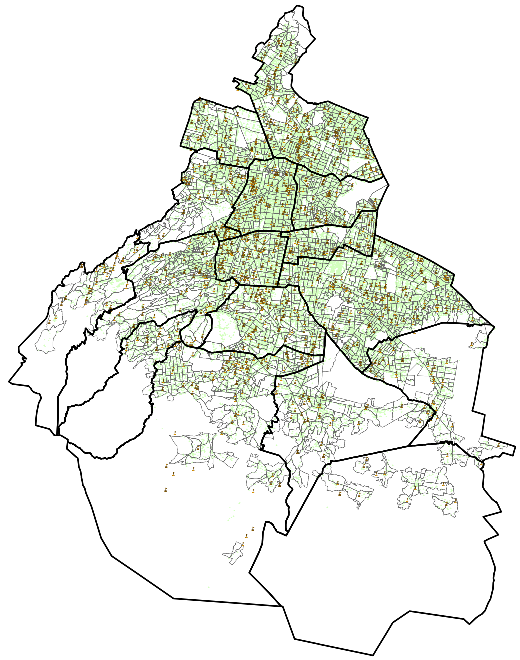
(b) Middle Schools and Firearm Injuries



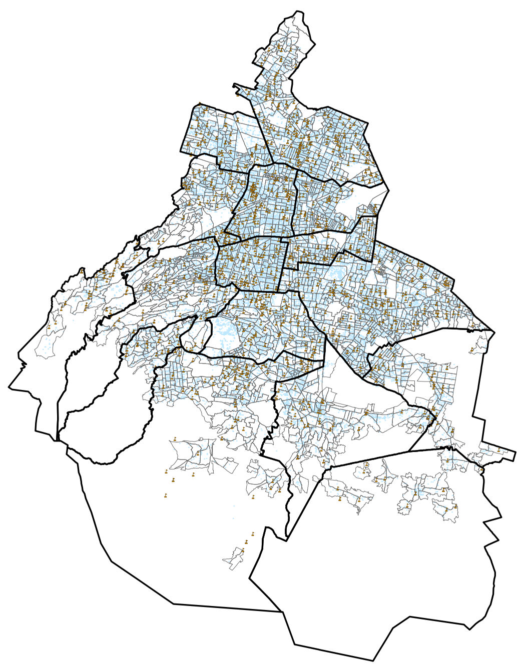
Notes: Each panel shows the geographic distribution of middle schools and violent crimes from January 2013 to September 2016. Panel (a) shows homicides (a total of 3,933) and middle-schools and Panel (b) shows firearm injuries (a total of 5,377) and middle-schools. Information on the geographic distribution of middle schools comes from the Ministry of Education and information on the geographic distribution of violent crimes comes from SSP-CDMX.

Figure A.2: Other Crimes and Middle Schools in Mexico City 2013-2016

(a) Middle Schools and Other-Violent Crimes



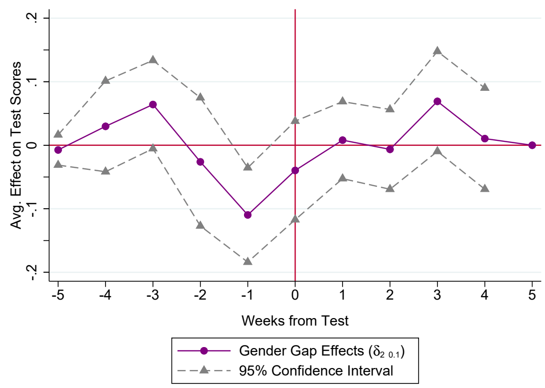
(b) Middle Schools and Non-Violent Crimes



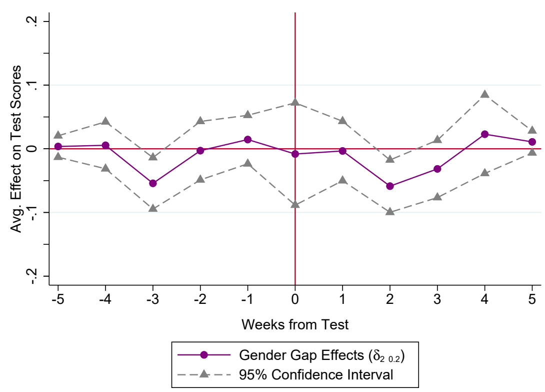
Notes: Panel (a) shows the geographic distributions of middle-schools and other-violent crimes (rapes and robbery with violence, a total of 80,899) and Panel (b) shows middle-schools and non-violent crimes (robbery without violence, a total of 42,481) from January 2013 to September 2016. Information on the geographic distribution of middle schools comes from the Ministry of Education and information on the geographic distribution of violent crimes comes from SSP-CDMX.

Figure A.3: Event Study Estimates of The Gender Gap Effect of Exposure to Violent Crime
Restricted Sample: Schools Ever Exposed to Violent Crime 4 Weeks Before or 4 Weeks After the Test

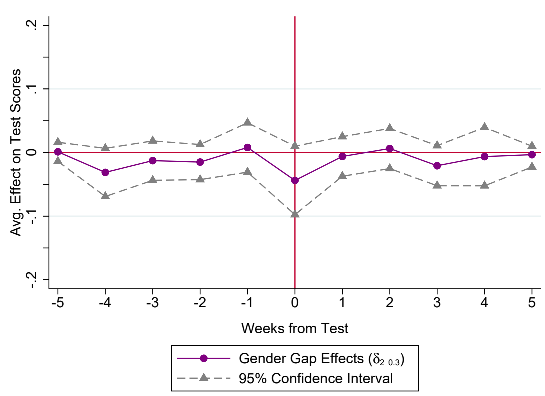
(a) 0.1 Miles



(b) 0.2 Miles



(c) 0.3 Miles



Notes: Each panel shows the event study estimates by weeks, for each distance-ring, of the gender gap effect of exposure to violent crime around the school *before*, *during*, and *after* the COMIPEMS test date, relative to the difference of being exposed to crime during 5 or more weeks after the COMIPEMS test for schools that were ever exposed to violent crime either during the 4 weeks *before* or 4 weeks *after* COMIPEMS test. All estimates are from a single regression.

Appendix B Tables

Table B.1: Estimated Effects on the Probability of Not Taking the Exam

	(1)
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	0.000
	(0.005)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	-0.007*
	(0.004)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	-0.003
	(0.003)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	0.004
	(0.003)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	0.002
	(0.003)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	0.001
	(0.003)
N	405065
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.188
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.603
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}} = 0$)	0.269

Notes: This specification includes school fixed effects, year fixed effects, a female indicator, school-specific time trends, school municipality-by-year fixed effects, and residence municipality-by-year fixed effects. Violent crimes include homicides and firearm injuries. Standard errors in parentheses are clustered at the school level. *, **, *** significant at the 10%, 5%, and 1% level, respectively.

Table B.2: Estimated Effects of Violent Crimes on Attrition by Weeks Before the Test

	1 week (1)	2 weeks (2)	3 weeks (3)	4 weeks (4)
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	0.017	0.003	0.001	0.000
	(0.012)	(0.011)	(0.009)	(0.009)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	0.001	-0.000	0.004	0.000
	(0.013)	(0.009)	(0.008)	(0.007)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	-0.009	-0.002	-0.001	-0.001
	(0.010)	(0.008)	(0.006)	(0.005)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	-0.007	0.001	-0.001	0.001
	(0.010)	(0.007)	(0.006)	(0.005)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	-0.001	-0.003	0.001	-0.001
	(0.008)	(0.006)	(0.005)	(0.004)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	-0.002	-0.000	0.001	0.002
	(0.008)	(0.005)	(0.004)	(0.004)
N	399025	399025	399025	399025
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.196	0.828	0.664	0.978
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.120	0.928	0.752	0.999
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}} = 0$)	0.751	0.654	0.661	0.943

Notes: All specifications include school fixed effects, year fixed effects, a female indicator, school-specific time trends, school municipality-by-year fixed effects, and residence municipality-by-year fixed effects. Violent crimes include homicides and firearm injuries. Standard errors in parentheses are clustered at the school level. *, **, *** significant at the 10%, 5%, and 1% level, respectively.

Table B.3: Estimated Effects of Violent Crimes on Test Scores by Weeks Before the Test
Restricted Sample: Schools Exposed to Violent Crime 4 Weeks Before or 4 Weeks After the Test

	1 week	2 weeks	3 weeks	4 weeks
	(1)	(2)	(3)	(4)
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	-0.007	0.008	-0.005	0.002
	(0.032)	(0.025)	(0.022)	(0.020)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	-0.111***	-0.067**	-0.031	-0.009
	(0.031)	(0.032)	(0.030)	(0.025)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	0.021	0.009	0.014	0.001
	(0.029)	(0.021)	(0.016)	(0.013)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	0.007	0.002	-0.018	-0.012
	(0.020)	(0.016)	(0.014)	(0.012)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	0.013	0.002	0.008	0.008
	(0.020)	(0.015)	(0.012)	(0.011)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	0.004	-0.003	-0.003	-0.008
	(0.022)	(0.013)	(0.011)	(0.010)
N	214494	214494	214494	214494
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.001	0.033	0.117	0.769
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.265	0.585	0.770	0.401
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}} = 0$)	0.358	0.905	0.666	0.999

Notes: All specifications include school fixed effects, year fixed effects, a female indicator, individual controls, school-specific time trends, school municipality-by-year fixed effects, and residence municipality-by-year fixed effects. Individual controls include academic ability (8th grade general GPA and math GPA fixed effects), parental education (mother's education and father's education fixed effects), and other characteristics (the number of books and the number of personal computers at home fixed effects). Violent crimes include homicides and firearm injuries. Standard errors in parentheses are clustered at the school level. *, **, *** significant at the 10%, 5%, and 1% level, respectively.

Table B.4: Estimated Effects on Schools Composition by Weeks Before the Test: Parental Education

	1 week (1)	2 weeks (2)	3 weeks (3)	4 weeks (4)
Panel A: Mother's Education (High School Diploma or Higher)				
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	0.019	0.009	0.012	0.003
	(0.013)	(0.013)	(0.010)	(0.010)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	0.007	-0.007	-0.001	0.002
	(0.017)	(0.013)	(0.011)	(0.012)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	0.004	0.002	0.003	-0.000
	(0.011)	(0.008)	(0.007)	(0.005)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	0.004	-0.000	-0.001	0.004
	(0.010)	(0.007)	(0.007)	(0.006)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	0.011	0.010*	0.007	0.003
	(0.009)	(0.006)	(0.005)	(0.005)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	-0.016*	-0.004	-0.010*	-0.007
	(0.008)	(0.006)	(0.005)	(0.005)
N	340105	340105	340105	340105
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.086	0.872	0.377	0.599
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.407	0.759	0.742	0.511
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}} = 0$)	0.564	0.311	0.603	0.428
Panel B: Father's Education (High School Diploma or Higher)				
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	-0.024	-0.013	-0.002	-0.003
	(0.017)	(0.013)	(0.011)	(0.010)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	0.031	0.013	0.001	0.002
	(0.022)	(0.018)	(0.014)	(0.012)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	0.007	0.002	-0.002	-0.001
	(0.012)	(0.009)	(0.007)	(0.006)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	-0.008	0.006	0.006	-0.001
	(0.012)	(0.009)	(0.008)	(0.006)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	-0.006	0.000	-0.002	-0.000
	(0.008)	(0.006)	(0.005)	(0.005)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	0.017*	0.003	0.007	0.002
	(0.009)	(0.007)	(0.006)	(0.005)
N	340105	340105	340105	340105
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.700	0.997	0.937	0.905
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.969	0.355	0.545	0.728
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}} = 0$)	0.201	0.657	0.370	0.739

Notes: All specifications include school fixed effects, year fixed effects, a female indicator, individual controls, school-specific time trends, school municipality-by-year fixed effects, and residence municipality-by-year fixed effects. Individual controls include academic ability (8th grade general GPA and math GPA fixed effects), parental education (mother's education and father's education fixed effects), and other characteristics (the number of books and the number of personal computers at home fixed effects). Violent crimes include homicides and firearm injuries. Standard errors in parentheses are clustered at the school level. *, **, *** significant at the 10%, 5%, and 1% level, respectively.

Table B.5: Estimated Effects on Schools Composition by Weeks Before the Test: Academic Ability

	1 week (1)	2 weeks (2)	3 weeks (3)	4 weeks (4)
Panel A: Cumulative GPA Lowest Quartile				
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	-0.030	-0.002	-0.011	-0.020
	(0.023)	(0.018)	(0.015)	(0.014)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	0.019	0.008	0.004	0.023
	(0.019)	(0.014)	(0.014)	(0.014)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	-0.003	-0.003	0.005	0.004
	(0.014)	(0.010)	(0.008)	(0.007)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	0.000	0.005	0.003	-0.000
	(0.009)	(0.008)	(0.007)	(0.007)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	0.004	-0.002	0.003	0.004
	(0.010)	(0.008)	(0.007)	(0.006)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	-0.002	0.008	-0.005	-0.005
	(0.010)	(0.007)	(0.006)	(0.005)
N	340105	340105	340105	340105
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.550	0.674	0.578	0.838
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.896	0.822	0.375	0.587
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}}$=0)	0.880	0.446	0.784	0.923
Panel B: Cumulative Math GPA Lowest Quartile				
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	-0.005	-0.008	0.002	0.006
	(0.030)	(0.021)	(0.017)	(0.015)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	0.011	0.007	0.017	0.009
	(0.019)	(0.015)	(0.012)	(0.011)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	0.023	0.009	-0.004	-0.004
	(0.014)	(0.011)	(0.009)	(0.008)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	-0.015	-0.010	-0.007	-0.006
	(0.011)	(0.008)	(0.007)	(0.006)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	-0.013	-0.009	-0.012	-0.011*
	(0.012)	(0.009)	(0.008)	(0.007)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	0.008	0.001	0.003	0.007
	(0.012)	(0.009)	(0.006)	(0.006)
N	340105	340105	340105	340105
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.809	0.963	0.250	0.305
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.615	0.954	0.206	0.179
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}}$=0)	0.736	0.427	0.283	0.567

Notes: All specifications include school fixed effects, year fixed effects, a female indicator, individual controls, school-specific time trends, school municipality-by-year fixed effects, and residence municipality-by-year fixed effects. Individual controls include academic ability (8th grade general GPA and math GPA fixed effects), parental education (mother's education and father's education fixed effects), and other characteristics (the number of books and the number of personal computers at home fixed effects). Violent crimes include homicides and firearm injuries. Standard errors in parentheses are clustered at the school level. *, **, *** significant at the 10%, 5%, and 1% level, respectively.

Table B.6: Estimated Effects on Schools Composition by Weeks Before the Test: Other Determinants of Performance

	1 week (1)	2 weeks (2)	3 weeks (3)	4 weeks (4)
Panel A: More than 50 Books at Home				
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	0.001	0.002	-0.006	0.007
	(0.015)	(0.011)	(0.010)	(0.009)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	-0.011	-0.007	0.001	-0.005
	(0.012)	(0.011)	(0.009)	(0.009)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	0.011	0.006	0.004	0.001
	(0.010)	(0.007)	(0.007)	(0.006)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	-0.017	-0.008	-0.006	0.003
	(0.013)	(0.009)	(0.008)	(0.006)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	0.002	0.001	0.004	0.002
	(0.009)	(0.006)	(0.005)	(0.005)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	0.005	-0.001	-0.003	-0.002
	(0.009)	(0.006)	(0.005)	(0.005)
N	340105	340105	340105	340105
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.507	0.643	0.687	0.834
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.574	0.823	0.755	0.445
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}} = 0$)	0.491	0.995	0.919	0.980
Panel B: At Least One Computer at Home				
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	0.021*	0.010	0.002	-0.000
	(0.013)	(0.013)	(0.011)	(0.010)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	0.006	-0.002	0.007	0.010
	(0.009)	(0.010)	(0.009)	(0.010)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	-0.015	-0.010	-0.007	0.001
	(0.010)	(0.007)	(0.006)	(0.005)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	0.003	0.007	0.005	-0.006
	(0.012)	(0.009)	(0.007)	(0.006)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	-0.004	-0.005	0.001	-0.001
	(0.008)	(0.006)	(0.005)	(0.004)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	-0.006	-0.002	-0.002	-0.001
	(0.008)	(0.006)	(0.005)	(0.004)
N	340105	340105	340105	340105
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.033	0.446	0.318	0.245
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.093	0.689	0.654	0.406
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}} = 0$)	0.157	0.180	0.917	0.634

Notes: All specifications include school fixed effects, year fixed effects, a female indicator, individual controls, school-specific time trends, school municipality-by-year fixed effects, and residence municipality-by-year fixed effects. Individual controls include academic ability (8th grade general GPA and math GPA fixed effects), parental education (mother's education and father's education fixed effects), and other characteristics (the number of books and the number of personal computers at home fixed effects). Violent crimes include homicides and firearm injuries. Standard errors in parentheses are clustered at the school level. *, **, *** significant at the 10%, 5%, and 1% level, respectively.

Table B.7: Estimated Effects on Test Scores by Weeks Before the Test and Poverty
Restricted Sample: Schools Ever Exposed to Violent Crime 4 Weeks Before or 4 Weeks After the Test

	Low Poverty				*High Poverty*			
	1 week	2 weeks	3 weeks	4 weeks	1 week	2 weeks	3 weeks	4 weeks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	-0.029	0.030	-0.002	0.003	-0.005	-0.021	-0.016	-0.002
	(0.071)	(0.041)	(0.031)	(0.024)	(0.039)	(0.034)	(0.032)	(0.033)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	-0.106***	-0.062	-0.019	-0.010	-0.117**	-0.070	-0.043	-0.009
	(0.031)	(0.039)	(0.035)	(0.028)	(0.049)	(0.055)	(0.050)	(0.044)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	0.042	0.001	0.021	0.011	0.014	0.019	0.018	0.003
	(0.028)	(0.031)	(0.022)	(0.018)	(0.045)	(0.030)	(0.024)	(0.019)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	-0.020	-0.013	-0.034*	-0.031*	0.027	0.011	-0.008	0.002
	(0.036)	(0.024)	(0.020)	(0.017)	(0.023)	(0.021)	(0.019)	(0.017)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	-0.002	-0.019	-0.007	-0.019	0.014	0.009	0.017	0.028*
	(0.032)	(0.021)	(0.017)	(0.016)	(0.027)	(0.021)	(0.017)	(0.015)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	-0.014	-0.009	-0.013	-0.023	0.027	0.007	0.007	0.005
	(0.030)	(0.017)	(0.017)	(0.015)	(0.029)	(0.018)	(0.014)	(0.012)
N	98355	98355	98355	98355	113129	113129	113129	113129
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.106	0.385	0.410	0.773	0.005	0.024	0.093	0.759
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.472	0.644	0.498	0.255	0.248	0.279	0.665	0.788
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}} = 0$)	0.558	0.157	0.244	0.007	0.090	0.358	0.127	0.018

Notes: All specifications include school fixed effects, year fixed effects, a female indicator, individual controls, school-specific time trends, school municipality-by-year fixed effects, and residence municipality-by-year fixed effects. Individual controls include academic ability (8th grade general GPA and math GPA fixed effects), parental education (mother's education and father's education fixed effects), and other characteristics (the number of books and the number of personal computers at home fixed effects). Violent crimes include homicides and firearm injuries. Standard errors in parentheses are clustered at the school level. *, **, *** significant at the 10%, 5%, and 1% level, respectively.

Table B.8: Estimated Effects on Test Scores by Weeks Before the Test and Crime Rate
Restricted Sample: Schools Ever Exposed to Violent Crime 4 Weeks Before or 4 Weeks After the Test

	Low Crime				*High Crime*			
	1 week	2 weeks	3 weeks	4 weeks	1 week	2 weeks	3 weeks	4 weeks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposed to Crime 0.1mile ($\delta_{1_{0.1}}$)	-0.051	0.012	0.005	0.023	-0.008	-0.027	-0.032	-0.022
	(0.047)	(0.039)	(0.039)	(0.038)	(0.053)	(0.033)	(0.023)	(0.020)
Exposed to Crime x Female 0.1mile ($\delta_{2_{0.1}}$)	-0.123***	-0.082**	-0.061	-0.027	-0.081	-0.046	-0.002	0.006
	(0.034)	(0.041)	(0.045)	(0.042)	(0.066)	(0.048)	(0.032)	(0.027)
Exposed to Crime 0.2mile ($\delta_{1_{0.2}}$)	-0.085	-0.042	-0.028	-0.019	0.044	0.039*	0.037**	0.017
	(0.062)	(0.031)	(0.025)	(0.021)	(0.031)	(0.023)	(0.018)	(0.016)
Exposed to Crime x Female 0.2mile ($\delta_{2_{0.2}}$)	0.023	0.009	-0.010	-0.011	-0.005	-0.006	-0.026	-0.012
	(0.024)	(0.020)	(0.019)	(0.018)	(0.028)	(0.023)	(0.019)	(0.017)
Exposed to Crime 0.3mile ($\delta_{1_{0.3}}$)	-0.018	-0.007	-0.003	0.008	0.020	-0.006	0.005	-0.003
	(0.033)	(0.023)	(0.018)	(0.016)	(0.024)	(0.018)	(0.016)	(0.015)
Exposed to Crime x Female 0.3mile ($\delta_{2_{0.3}}$)	0.017	0.000	0.009	-0.000	0.003	-0.000	-0.011	-0.013
	(0.031)	(0.020)	(0.015)	(0.014)	(0.029)	(0.017)	(0.015)	(0.013)
N	95628	95628	95628	95628	113630	113630	113630	113630
p-value ($\delta_{1_{0.1}} + \delta_{2_{0.1}} = 0$)	0.002	0.102	0.161	0.931	0.160	0.070	0.198	0.531
p-value ($\delta_{1_{0.2}} + \delta_{2_{0.2}} = 0$)	0.317	0.328	0.175	0.172	0.100	0.085	0.492	0.751
p-value ($\delta_{1_{0.3}} + \delta_{2_{0.3}} = 0$)	0.980	0.736	0.730	0.648	0.377	0.745	0.707	0.284

Notes: All specifications include school fixed effects, year fixed effects, a female indicator, individual controls, school-specific time trends, school municipality-by-year fixed effects, and residence municipality-by-year fixed effects. Individual controls include academic ability (8th grade general GPA and math GPA fixed effects), parental education (mother's education and father's education fixed effects), and other characteristics (the number of books and the number of personal computers at home fixed effects). Violent crimes include homicides and firearm injuries. Standard errors in parentheses are clustered at the school level. *, **, *** significant at the 10%, 5%, and 1% level, respectively.