IEB Working Paper 2025/07

CRIME AT YOUR DOORSTEP: GENDER-SPECIFIC EFFECTS ON UNIVERSITY STUDENT PERFORMANCE

Daniel Montolio, Pere A. Taberner

Version May 2025

Public Policies

IEB Institut d'Economia de Barcelona

CRIME AT YOUR DOORSTEP: GENDER-SPECIFIC EFFECTS ON UNIVERSITY STUDENT PERFORMANCE

Daniel Montolio, Pere A. Taberner

The **Barcelona Institute of Economics (IEB)** is a research centre at the University of Barcelona (UB) which specializes in the field of applied economics. The IEB is a foundation funded by the following institutions: "La Caixa" Foundation, Saba, the Barcelona City Hall, the Barcelona Metropolitan Area, the University of Barcelona, the Autonomous University of Barcelona, the Barcelona Provincial Council, Agbar, Cuatrecasas, Consorci Zona Franca Barcelona and Fundación Miquel y Costas.

The **IEB** research program in **Public Policies** aims at promoting research related to the design, implementation and evaluation of public policies that meet social needs and enhance social and individual welfare. Special emphasis is put on applied research and on work that tries to shed light on the Economics of Education, Health Economics, Innovation, Labour Markets and Security Policies. Disseminating research findings in these topics to a broader audience is also an aim of the program.

Postal Address:
Institut d'Economia de Barcelona
Facultat d'Economia i Empresa
Universitat de Barcelona
C/ John M. Keynes, 1-11
(08034) Barcelona, Spain
Tel.: + 34 93 403 46 46
ieb@ub.edu
http://www.ieb.ub.edu

CRIME AT YOUR DOORSTEP: GENDER-SPECIFIC EFFECTS ON UNIVERSITY STUDENT PERFORMANCE[1]

Daniel Montolio, Pere A. Taberner

ABSTRACT: Student performance at university significantly influences individual decisions and future opportunities, especially in labour markets. This paper analyses the impact of local crime on student performance during higher education, with a focus on potential gender differences. Following students over their bachelor's years, the identification strategy exploits granular local crime variation – violent and non-violent crimes – near students' residences before sitting a final exam. We consider both spatial and temporal patterns of crime exposure by estimating a panel data model with student, exam and district-month fixed-effects to provide causal estimates. Our findings suggest that violent crimes have a negative impact on student performance, while non-violent have no significant effect. Notably, the results are mainly driven by high-ability female students, with suggestive evidence that male students in the bottom or middle parts of the grade distribution are also affected.

JEL Codes: A22, I23, J16, K42
Keywords: local violent crime, academic performance, higher education, gender differences

Daniel Montolio
Universitat de Barcelona & IEB
E-mail: montolio@ub.edu

Pere A. Taberner
Universitat de Barcelona & IEB & KSNET
E-mail: peretaberner@gmail.com

[1]*We would like to thank Xavier Tibau and Claudia Serra for their data support. We are also grateful to Laia Bosque-Mercader, Anastasia Terskaya, Matteo Sandi, and participants in the XXXII Public Economics Meeting for very valuable comments and feedback. Thanks to the Faculty of Economics and Business of the University of Barcelona for the data, especially to José Luís Andújar. Daniel Montolio acknowledges financial support from the Spanish Ministry of Science, Innovation and Universities under the project PID2022-140661OB-I00. All remaining errors are our own.

1 Introduction

Higher education, the last step in formal education, plays a crucial role in helping students learn new ways of thinking and acquire problem-solving skills. At this educational stage, students are supposed to achieve high levels of knowledge and different types of skills (from technical to oral and communication skills) that will likely translate into better labour market opportunities and, ultimately, higher job success. A better understanding of the (external) determinants of student performance at the university level and its possible impact on gender differences might contribute to understanding observed labour outcomes and designing better policies to reduce (educational) inequalities caused by those external factors.

In this vein, one crucial external factor that can influence student performance is exposure to violence or crime. Note that exposure to violence or crime is not only considered as being directly victimized, but also witnessing, being told, or hearing about a crime (Buka et al., 2001) or, in a broader sense, living in a violent environment or being involved in violent situations (Sharkey, 2018). Various studies have shown that being exposed to violence and crime may negatively impact cognitive processes (Sharkey et al., 2014; Sharkey and Sampson, 2017; Ang, 2020; Chang and Padilla-Romo, 2022) as a result of mental health and well-being deterioration (Cornaglia et al., 2014; Dustmann and Fasani, 2016; Bencsik, 2020); deterioration that in turn may be caused, among other factors, by an increase in sleeping difficulties (Morrall et al., 2010), concentration problems (Chang and Padilla-Romo, 2022), loss of self-confidence (Morrall et al., 2010; Dustmann and Fasani, 2016), or the presence of fear and worry (Sharkey et al., 2014). As a result, these adverse effects on individual cognitive processes can also negatively impact students' learning and assessment processes. At the university level, where assessment is generally subject to higher degrees of pressure and the stakes are higher, these impacts can be even more significant and amplified.

Moreover, a growing body of literature highlights significant gender disparities in crime-related issues, such as variations in fear of crime or perceived risk of victimization. Research consistently shows that women report higher levels of fear and perceived vulnerability to crime compared to men (see for example, Valera and Guàrdia, 2014; Cops and Pleysier, 2011; Henson and Reyns, 2015), which may have broader implications for cognitive functioning and learning processes. In addition, women are more likely to alter their daily routines or behaviors as a precautionary measure (Johansson and Haandrikman, 2023), which could disrupt their study patterns and academic performance. Therefore, these gender-specific differences related to crime issues provide a robust justification to investigate whether and how local crime exposure affects male and female students differently in educational settings.

In this paper, we analyse the impact of local crime on student performance at the university level and the potential existence of gender differences in such impact. We distinguish between violent and non-violent crimes, since violent ones (more salient) could be those more likely to disrupt students' learning processes. To do so, we combine a georeferenced dataset of all crimes committed in the Metropolitan Area of Barcelona (MAB) with academic and sociodemographic information of students enrolled at the Faculty of Economics and Business of the University of Barcelona. Following students over their bachelor's years, the identification strategy exploits granular within-student variation in exposure to crime when sitting final exams over time. We thus perform panel data estimations with student, exam, and spatial trends fixed-effects to effectively identify the causal impact of crime on academic grades.

We find that violent crimes near students' homes negatively affect student performance on their final exams, whereas non-violent events have no significant impact on students' grades. These differences suggest that more salient crimes can be more noticeable to students and thus have a more significant impact on their performance. We also show spatial and time trends since the magnitude of the impact reduces as the distances from students' homes and the number of days before examinations increase. Notably, the results are primarily driven by high-ability female students, with suggestive evidence that male students are more likely to fail a final exam as violent crimes increase in our measures of exposure to crime. These findings remain robust to selection bias related to exam participation since we demonstrate that violent and non-violent crimes do not discourage students from taking their final exams.

Related studies have analysed the causal link between crime and education performance, focusing mainly on the school rather than the university level. Moreover, this literature primarily focuses on developing countries and highly violent crimes (such as murders and homicides) that are not that common in developed countries. To our best knowledge, only one study analyses this issue in a major European city, London, and takes into account more common typologies of crime (Facchetti, 2021). This study relies on cross-sectional aggregate data with students' zip codes and a standardised test at the end of primary education. Therefore, our study provides new evidence in the field by focusing on university students in a developed urban environment and by using panel data to capture temporal and spatial exposure to crime with the exact addresses of students.

Furthermore, existing literature on gender differences in crime exposure effects on educational outcomes is mixed. Some authors find that male students are more affected by homicides than their female counterparts (Koppensteiner and Menezes, 2019; Haugan, 2016), while other authors suggest that female students are more affected (Facchetti, 2021; Chang and Padilla-Romo, 2022). In contrast, some studies find no differences across genders (Beland and Kim, 2016; Brück et al., 2019; Monteiro and Rocha, 2017). Moreover, Haugan (2016) indicates that these differences might depend on the subject under study, such as Maths, Chemistry, or Philosophy. Thus, we provide more evidence of the potential heterogeneity of results regarding student gender.

The rest of the paper is structured as follows. Section 2 reviews the most recent and related literature on the topic. Section 3 describes the background and the educational setting. Section 4 outlines the empirical strategy, and Section 5 reports the results and identifies the possible mechanisms responsible for the results obtained. Finally, the last Section 6 discusses the results and presents the main conclusions.

2 Literature review

This paper lies in the intersection between the economics of crime and the economics of education literature. On the one hand, several studies have analysed crime's direct and indirect costs on society and individuals. For instance, the economics of crime literature has deeply studied the effects of crime at the individual level, such as on economic activity (Cabral et al., 2020; Bharadwaj et al., 2021; Deb and Gangaram, 2023), mental health (Dustmann and Fasani, 2016; Bencsik, 2020) or physical health (Wilson et al., 2022; Currie et al., 2018; Neanidis and Papadopoulou, 2013). On the other hand, the economics of education literature has analysed the impact of external shocks on learning outcomes, such as air pollution (Ebenstein et al., 2016; Austin et al., 2019; Heissel et al., 2020), environmental temperature (Cho, 2017; Park, 2022; Graff Zivin et al., 2020) or natural disasters (Harris and Larsen, 2022). As expected, contributions have also linked both strands of the economic literature and analysed the impact of crime and violence on student performance.

In this regard, a body of economic literature focuses on extreme violent crimes in developing countries, such as conflict violence, armed conflicts, gunfights, or homicides. Monteiro and Rocha (2017) assess the impact of gunfights related to drugs trafficking gangs around schools on national standardised test scores in Rio de Janeiro, Brazil. They exploit differences in these violent crime rates across space and time with a pooled cross-section data structure. Their results indicate negative impacts on student scores, and they turn even more damaging when gunfights are closer to the school, to exam dates, or for longer gang conflict duration. Koppensteiner and Menezes (2019) and Haugan (2016) also study the impact of children's exposure to homicides on educational outcomes. Koppensteiner and Menezes (2019) develop a pooled cross-section framework, with school and time-fixed effects and within-school trends, with primary schools and homicide information in Sao Paulo, Brazil. They find that violence near the school negatively impacts standardised test scores, attendance, and dropout rates. However, violence around their residence only affects dropout rates. Likewise, Haugan (2016) develops a similar econometric strategy with data from Medellin, Colombia. He also finds that homicides around the school harm student performance in standardised tests.

Similarly, Chang and Padilla-Romo (2022) analyse the impact of homicides and firearm injuries around the school on high-stake tests in Mexico City. They compute non-overlapping buffer rings of 0.1, 0.2, and 0.3 miles to create a dummy variable which indicates whether a violent crime occurred in the week before the tests.[1] They find that female students are affected by this type of violent crime, while male students are not. According to their results, female students suffer concentration problems when a crime occurs near their school. Finally, Brück et al. (2019) analyse the impact of conflict violence around students' schools on educational outcomes in Palestine. Using a repeated cross-section approach, they exploit within-school variation in the number of fatalities over the academic year. Their findings indicate a negative impact of conflict violence on students' probability of passing a final exam, being admitted to the university, and exam scores. However, they do not find a significant impact among top-performing students, and they do not find gender differences.

There are also few papers in developed contexts. Ang (2020) performs a difference-in-differences analysis in Los Angeles to find that students' exposure to police violence (defined as police killings) around their home (half a mile) decreases their Grade Point Average (GPA) and hurts their mental health. However, this study does not examine potential differential impacts by gender. Similarly, Beland and Kim (2016) analyse how school shootings affect high-school

[1] In a robustness check, they re-estimate the main analysis with different time windows before exams: 2, 3 and 4 weeks.

student performance in California. Results show that students who witness a shooting in their school get lower scores than similar pupils without such a traumatic experience. However, they do not find an impact on graduation, failure, and attendance rates. Still, these types of crimes are less common in other developed countries. Ultimately, Aizer (2013) analyse neighbourhood violence on children outcomes in Los Angeles, USA. She performs a cross-section analysis of children, families, and neighbourhood characteristics with crime data at zip code and census tract levels. She also estimates different models with families and neighbourhood fixed effects. She finds little evidence of the negative impact of violence around students' neighbourhoods on cognitive test scores and behaviour problems. Moreover, she suggests the relevance of controlling for neighbourhood and family characteristics since disadvantaged environments suffer higher crime levels.

To our best knowledge, the only paper analysing a European setting is Facchetti (2021), which uses a broader definition of crime, including non-extreme crimes. Facchetti (2021) analyses the impact of being exposed to crime on the standardised tests at the end of primary school in London, relying on a pooled cross-section data structure of six cohorts of students taking these high-stake examinations, and she measures crime rates at the postal code level. Concretely, Facchetti (2021) computes the crime variable as the standardised number of crimes within 500 meters around students' postal code over the complete academic year. She finds a negative impact on standardised test scores at the end of primary school and no differences of this impact across gender.

The mixed evidence regarding the gender-specific impacts of crime on educational outcomes motivates further investigation into these differentials. In this regard, a body of literature has identified various factors underlying gender differences in responses to crime, such us fear of crime and perceived risk of victimization. One prominent explanation is the vulnerability thesis (Jackson, 2009) which suggests that women perceive themselves as more physically and socially vulnerable to crime. This perceived vulnerability is linked to factors such as physical strength disparities, heightened awareness of potential victimization, and a pervasive sense of powerlessness in dangerous situations—particularly in cases involving sexual assault. Ferraro (1996) discussed the shadow of sexual assault hypothesis which argues that the constant risk of sexual violence amplifies women's fear of crime. Consequently, even when considering non-sexual crimes, women's perceptions are often influenced by the possibility that any victimization might escalate into sexual assault. This leads to greater levels of fear in public spaces, especially in environments perceived as unsafe.[2]

In a nutshell, our study contributes to the field by focusing on crime exposure of university students in a developed setting where the typologies of crimes are different from those in the USA or developing countries. Moreover, we consider a broader definition of violent and non-violent crimes and not only focus on a few types of crimes. We provide a more granular understanding of how exposure to crime near students' residences influences exam outcomes by using a panel data framework, and we analyse spatial and time patterns. Our findings also add to the literature on gendered responses to crime exposure, showing distinct impacts for male and female students. Therefore, our study provides a better understanding of the im-

[2] Moreover, urban and environmental studies have shown that women experience greater fear in urban settings with poor lighting, low visibility, and signs of disorder (Johansson and Haandrikman, 2023).

pact of external and short-term shocks on student performance (the educational production function) and gender differences on educational outcomes.

3 Institutional background and data

We focus on the results obtained in all final exams taken by a sample of students from the bachelor's degree in business administration (BBA) at the University of Barcelona from 2007 to 2010.[3] The reason for selecting this period is that it corresponds to the period right before the implementation of the Bologna Process, that is, a period when course evaluations were characterized by a single final exam. Indeed, before the adoption of the European Higher Education Area (EHEA) guidelines — Bologna Process — the standard way to evaluate students was the single assessment (SA). This evaluation system provided lectures over the term, and, at the end of it, knowledge was assessed in a single high-stake final exam, for which we know the day and time it took place.[4]

Over the years under analysis, the four-year bachelor's degree was divided into two terms each academic year.[5] Students had lectures in the first term from September to December, with final examinations in January (first call). Similarly, students had lectures for the second term from February to May, with final examinations in June (first call). Students pass a course when they obtain a grade of 5 or higher on a numeric scale from 0 to 10, with 0 being the lowest and ten the highest grade.[6]

3.1 Student data

The Faculty of Economics and Business at UB provided us with the administrative information — demographic and academic information — for our student sample. The demographic information of each student contains the gender, current address, date and place of birth, nationality, and student ID. The academic data includes general information about the whole undergraduate program and specific information for each academic year. The general information includes the student's access path to the degree, university access grade, the year of starting the degree, and the final GPA. The specific information for each academic year contains the number of cumulative credits passed – including courses enrolled and those passed (course title, group, term, and final grade) – and whether that academic year the student obtains a scholarship. All

[3]The sample of students corresponds to those enrolled in a compulsory third-year course in the academic year 2008-2009, for which we have both the place of residence and access to all grades over their Bachelor's studies. See section 3.1 for more details.

[4]The Bologna Process introduced the continuous assessment (CA), with a variety of assessment activities (midterms) that constituted the final grade of students for which we do not have an official calendar nor specific results of midterms.

[5]Our analysis period comprises four academic years, but it is not necessarily from the beginning to the end of students' studies. The reason is that students are can follow different paces and may retake courses over the years, taking more than four years to complete their bachelor's degree.

[6]In the event of failing a final exam (and thus, the course) or not taking it, students had a second opportunity — the 'second call, retake, or resit' — after the summer holidays, in September, before starting the following academic year. We focus only on the first call of final exams since all enrolled students are eligible to take the final exam in the first round. Additionally, it is worth noting that students who usually take the 'second call' represent a specific subset of the entire student population.

this administrative data allows us to have deep information about individual characteristics from a personal and an academic point of view.

We have 1,031 students with unique addresses, 282 outside the MAB. Some are located outside the province of Barcelona (102 students), and the rest, 180 students, are in the province of Barcelona but not in the MAB. We do not consider these 282 addresses because they imply high commuting times (more than 2 hours per day).[7] Therefore, we restrict our final sample to 749 students. It is important to highlight that 18 students (out of these 749 students) never took any final exam in the first call. Despite that, we include them in our analysis because they are needed when examining potential selection for taking the final exams.

Table 1 shows our final sample's main socioeconomic and educational descriptive statistics. Almost 55% of these students are female, which is statistically significantly different from the share of males. The average age (reference 2007) is 23 years old, and the median is 22 years old, with no statistically significant differences across genders. The 96.5% have Spanish nationality, with no statistically significant differences across genders. Moreover, female students outperform male students in the university entrance exams, statistically significant at the 5% level.

Table 1: Main descriptive statistics of students.

	All	**Female**	**Male**	**Statistic (diff Female - Male)**
No. of students	749	411	338	–
Gender (%)	–	54.87	45.13	2.67***
Age (mean)	23.15	22.95	23.40	-1.46
Age (median)	22.00	22.00	22.00	0.3
Spanish Nationality (%)	96.53	96.11	97.04	-0.7
University entrance grade (out of 10)	5.61	5.78	5.40	2.11**
No. of enrolled courses (annual average)	8.81	8.81	8.81	0.03
No. of finals exams taken (annual average)	6.77	6.95	6.54	1.84*
% of exams taken (annual average)	74.41	76.79	71.51	2.79***
% of exams passed (annual average)	59.57	60.76	58.13	1.68*
Final bachelor grade (out of 4)	1.31	1.34	1.27	4.13***

Note: The null hypothesis for the proportion test of gender is that the proportion of female students is equal to 50%, Z-statistic. The null hypothesis for the other proportion tests (% Spanish nationality, % of exams taken and % of exams passed) is that the proportion of females is equal to the proportion of males, Z-statistic. The null hypothesis for the Mean Test (age, bachelor final grade, university entrance grade, no. of enrolled courses and no. of final exams taken) is the equal mean across genders (unequal variances), t-statistic. The Median Test is a non-parametric 2-sample test in which the null hypothesis is equal medians across gender, chi-squared test statistic with continuity correction. *** denotes significance at 1% level, ** the 5% level and * the 10% level.

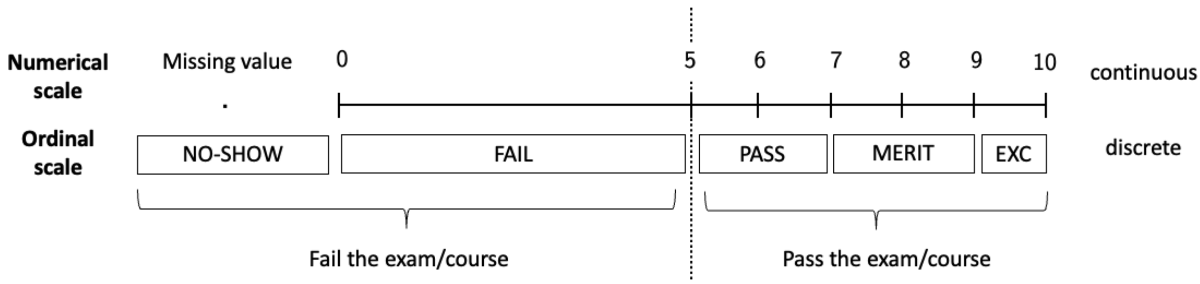
Analysing the educational variables, the annual average number of enrolled courses is almost nine, with no differences by gender. However, on average, female students sit the final exam of 6.95 courses, and male students 6.45, statistically significant at the 10% level. This fact means that female students take a higher proportion of enrolled final exams than male students,

[7] Anecdotal evidence suggests that some students who move to Barcelona to study at the university might have given their family address when enrolling instead of their new one in Barcelona.

statistically significant at the 1% level. Moreover, female students passed a higher proportion of final exams than male students, 60.76% and 58.13%, respectively, difference statistically significant at the 10% level. Finally, following the same pattern as university entrance exams, female students slightly outperform male students in the final bachelor grade, statistically significant at the 1% level.

We measure student performance using students' final examination grades. In the administrative student dataset, these grades were recorded on an ordinal scale. The numerical grades, from 0 to 10, were administratively converted to an ordinal scale of five possible values before being recorded in the transcript of grades: *no-show*, *fail*, *pass*, *merit*, and *excellent*, losing the valuable information of the numerical continuous grade. Therefore, students with a grade of 4.9 or lower were marked as *fail*, between 5 and 6.9 a *pass*, between 7 and 8.9 a *merit*, 9 or higher were marked as an *excellent*.[8] The grade translation between the numerical and ordinal scales is visually depicted in Figure 1.

Figure 1: Translation between numerical and ordinal grade scales



Source: own elaboration.

Our main dependent variable is, hence, the ordinal grade variable with four possible values (fail, pass, merit and excellent). From this variable, we derive other educational outcomes of interest; i) a dummy variable that takes a value of 1 if the student sat the final exam and 0 otherwise, ii) a dummy variable that takes a value of 1 if the student sat the exam and passes the exam and 0 otherwise (no-show is coded as missing value), and iii) a dummy variable that takes a value of 1 if the student sat the exam and obtained an excellent or an excellent with honours and 0 otherwise (no-show is coded as missing value).

Even if the full distribution of grades contains more information, it is interesting to also analyse the impact of local crime on the probability of passing an exam, or on the occurrence of high performance situations by students. Regarding the latter, the literature has shown that top-performing (or high-ability) students might be more sensitive to external factors (Beilock, 2011), such as test pressure (Montolio and Taberner, 2021), competition (Iriberri and Rey-Biel, 2019) or time pressure (De Paola and Gioia, 2016). Note that with the dummy variable informing about sitting a final exam we can analyse a possible mechanism and assess if local crime discourages students from attending final exams. The potential effect of local crime events on

[8]Within the group of students with an excellent those students with the best grade of their group obtained the grade of *excellent with honours*. Since this is a relative grade, which depends on the grade of their group, we decide not to take it as a category itself. For instance, a student taking a 9 might not have honours since it is not the best grade in their group, while another student with the same grade might have honours because it is the best grade in the group.

the grade distribution could also be affected by examination attendance and, thus, could bias our estimates. For this reason, if we have a selection into examinations, we might address it in our empirical strategy. However, no additional analysis or correction might be needed if we show that local crime does not discourage students from taking the exam (see Section 4.1).

Table 2 shows the distribution of the ordinal grade of all the final examinations, with and without the inclusion of no-shows. First, 23.0% of final exams were not taken by the students. Second, the most frequent grade was Pass, 30.2% when including no-shows and 39.2% when excluding them. Third, the grade with a smaller proportion was Excellent, 3.8% with no-shows and 5.0% without. Finally, gender differences in grade distributions are statistically significant at the 1% level, with and without no-shows. Male students show a higher no-show rate (25.4%) than females (21.0%), indicating lower exam attendance. Furthermore, females outperform males in higher grade categories, specifically in Merit and Excellent.

Table 2: Distribution of the ordinal grade variable

	With no-show (%)			Without no-show (%)		
	All	Female	Male	All	Female	Male
No-show	23.0	21.0	25.4	-	-	-
Fail	29.0	29.0	29.1	37.7	36.7	38.9
Pass	30.2	30.3	30.1	39.2	38.4	40.3
Merit	14.0	15.1	12.6	18.1	19.1	16.9
Excellent	3.8	4.6	2.9	5.0	5.8	3.9
Distribution differences across gender (p-value)			0.00			0.00
Observations	24,434	13,418	11,016	18,821	10,599	8,222
Students	749	411	338	731	400	331

Notes: Gender differences in grade distribution are tested using Chi-Square Test, Mann-Whitney Test, Kolmogorov-Smirnov Test, and an ordinal logistic regression. All tests lead to consistent results. Source: own elaboration from the student data.

3.2 Crime data

The crime database was provided by the *Mossos d'Esquadra* (the regional Catalan police) and contains georeferenced information on all the crimes committed in the region of Catalonia from 2007 to 2011. We have the date, the coordinates and the category of each crime committed in Catalonia. The richness of this detailed crime data allows us to distinguish crime typologies and define two main types of crime: violent and non-violent. Violent crimes are more likely to be perceptible to neighbouring communities and the students living there. Less prominent crimes, such as non-violent crimes, might be less noticeable to students without disturbing their studying processes. Therefore, violent incidents include robbery, injuries, threats, gender and sexual violence, family crimes, murder and other crimes against the person. Non-violent incidents include theft, car theft, damages, fraud, road safety, law order, drugs and environmental crimes.[9]

Table 3 shows that non-violent crimes are the most common type of crime — 78.9% — across MAB over the analysis period. Violent crimes (mainly crimes against the person) are less common, representing 21.1% of the total crimes. The last two columns show the detailed categories of crime. First, thefts (considered non-violent) are the most common crimes in the MAB, with almost half of the total crimes committed. Second, robbery (violent crime) is the second most common crime and car theft (non-violent) is the third most common crime. The following two most common crimes are also non-violent crimes: damages and fraud. The next ones are injuries and threats, both categorized as violent crimes, which constitute only 2.9% and 2.5%, respectively.

Table 3: Crime categories over the period 2007-2010 in the MAB.

Crime Category	**Share**	**Detailed category**	**Detailed share**
Non-violent crimes	78.9%	Theft	48.7%
		Car Theft	11.7%
		Damages	9.1%
		Fraud	4.5%
		Road safety	2.4%
		Law order	1.9%
		Drugs	0.6%
		Environment	0.1%
Violent crimes	21.1%	Robbery	12.4%
		Injuries	2.9%
		Threats	2.5%
		Gender and sexual violence	2.3%
		Family	0.7%
		Other crimes against person	0.3%
		Murder	0.1%
Total	100%		100%

Source: Own elaboration from *Mossos d'Esquadra* database.

We now examine the gender of victims across different types of crime. Table 4 indicates that women experience a slightly higher number of crimes as victims (53.3% female vs. 46.7% male) over the period 2007 and 2010 around the MAB. However, significant differences arise when we analyse the gender distribution of victimization according to the type of crime. Women represent a higher proportion of victims in crimes such as theft (59.7%) and threats (55.0%) and they are overwhelmingly affected in cases of gender and sexual violence (87.9%) and crimes against the family (72.9%). In contrast, men are disproportionately victimized in more violent crimes such as murder (72.1%), injuries (68.1%), and road safety offenses (68.2%). Additionally, crimes like car theft (65.2%), damages (63.4%), and drug-related offenses (59.8%) also show a higher prevalence of male victims. Therefore, women are more likely to be victims of personal and domestic-related crimes, while men are more frequently affected by violent and property

[9]We estimate several robustness checks with slightly different definitions to verify whether the results depend on the main typologies of crimes defined.

crimes with a physical confrontation component. This gender-based variation in victimization suggests that the psychological and academic consequences of crime exposure may differ by gender and crime type.

Table 4: Gender distribution of victimization across detailed crime categories

Detailed category	**Female (%)**	**Male (%)**
Theft	59.7	40.3
Car Theft	34.8	65.2
Damages	36.6	63.4
Fraud	43.5	56.5
Road Safety	31.8	68.2
Law & Order	48.1	51.9
Drugs	40.2	59.8
Environment	50.0	50.0
Robbery	48.1	51.9
Injuries	31.9	68.1
Threats	55.0	45.0
Gender and Sexual Violence	87.9	12.1
Against Family	72.9	27.1
Murder	27.9	72.1
Total	**53.3**	**46.7**

Source: Own elaboration from *Mossos d'Esquadra* database.

We measure the exposure to local crime for each student at the time of each eligible final exam. Specifically, we focus on crime events occurring near their homes in the previous days of each final exam. For this, we calculate the total number of crime incidents reported in an area of radius M meters from each student's place of residence over the previous D days. Specifically, M includes distances of $\{20, 40, 60, 80, 100, 300\}$ meters, while D can be 7, 15, or 30 days. This approach allows us to examine multiple spatial and temporal variables. In other words, we aggregate reported crime incidents based on these selected spatial and temporal parameters for each student-exam pair. This process results in 18 distinct measures of local crime exposure (6 distances and 3 pre-exam periods) for each final exam taken by each student. Since we want to differentiate violent and non-violent crimes, we compute 36 different measures of exposure to local crime, 18 variables for violent incidents and 18 for non-violent.

Figure 2 shows a visual example of this computation process. Small points represent crime locations over 7 days, and the square marker indicates a hypothetical address (for confidentiality). The solid circle has a radius of 80 meters, and all small points within it count as crimes committed in an area of an 80-meter radius over 7 days. Similarly, the dashed circle represents a radius of 100 meters, gathering all crimes within this area (also including those within the solid circle). These variables allow us to effectively measure exposure to crime and analyse how results and impact magnitudes vary according to the area and the time horizon taken into account.

Table 5 shows the main descriptive statistics of these 36 crime variables. As expected by the definition of each variable, as both the radius and the number of days included in the

Figure 2: Visualization of the computation of the crime variables

Notes: Solid circle has a radius of 80 meters and dashed circle is 100 meters. Small points represent crime locations over 7 days, and the square marker indicates a hypothetical address (for confidentiality). Source: Own elaboration from *Mossos d'Esquadra* database.

crime exposure variable increase, the average number of crimes rises consistently for both violent and non-violent incidents. This pattern occurs because each larger radius encompasses the previous smaller one, and each extended time period includes the previous, shorter interval. Overall, the table highlights notable differences between violent and non-violent crime exposures. Non-violent crimes generally show higher mean values across all distances and time periods compared to violent crimes. These patterns are expected given that the majority of crimes reported in the MAB area are non-violent (as shown in Table 3). This prevalence of non-violent crime around MAB reflects typical urban crime distributions, where crimes against property or minor infractions are committed more frequently than violent offences. This table provides context to our study since exposure to non-violent crimes may be more frequent, but exposure to violent crime might carry a different psychological impact.

Table 5: Mean of the crime variables computed to measure exposure to violent and non-violent crime

	Violent crime			Non-violent crime		
Radius	7 days	15 days	30 days	7 days	15 days	30 days
20 metres	0.01	0.02	0.04	0.03	0.06	0.13
40 metres	0.05	0.11	0.22	0.15	0.32	0.66
60 metres	0.11	0.24	0.48	0.35	0.74	1.49
80 metres	0.19	0.40	0.82	0.58	1.24	2.49
100 metres	0.28	0.61	1.25	0.91	1.92	3.85
300 metres	2.59	5.54	11.14	8.69	18.54	37.07

No. of students: 749

No. of student-exam pairs: 24,434

Notes: Mean is computed based on crime incidents within an area of the specified radius over time periods around student place of residence. The number of students and the number of student-exam pairs is the same for every single variable. Source: Own elaboration from *Mossos d'Esquadra* and student databases.

4 Empirical strategy

The identification strategy seeks to find the causal link between being exposed to crime around students' residence and their performance when sitting final exams at university. We rely on a panel data framework in which we observe the same students taking final exams over four academic years of their undergraduate studies.[10] Therefore, we exploit within-student variation in exposure to violent and non-violent crime over their final examinations.

As explained in Subsection 3.1, our main student performance outcome is an ordinal grade variable with four possible categories (fail, pass, merit and excellent). Thus, an ordered logit model (OLM) is a better alternative than a linear model since we do not need the linear assumption holding. However, estimating an ordered multinomial logit panel data (OLPD) with high dimensional fixed effects (HDFE) implies a really demanding estimation with the need for powerful computational resources. The random-effects (RE) estimator is the easiest to implement from a computational point of view. Still, it implies a strong assumption: independent variables are not correlated with time-invariant unobserved variables. On the other hand, the fixed-effects (FE) estimator relaxes this restriction, and the assumption that regressors are correlated with time-invariant variables is no longer needed. Moreover, it estimates an intercept for each cross-sectional unit, giving flexibility in the differences among units.

The FE estimator for OLPD is not straightforward and might lead to inconsistent and biased estimates (Baetschmann et al., 2020). Thus, the econometric literature has discussed two main estimators which lead to consistent and unbiased estimates: the BUC estimator (Baetschmann et al., 2015) and BUC_τ estimator (Baetschmann, 2012). The BUC_τ estimator is more precise and restrictive since it assumes constant thresholds among categories of the dependent variable, while the BUC estimator does not. The BUC estimator is derived from the conditional maximum likelihood (CML) estimator; this is for binary dependent variables. However, BUC_τ and BUC estimators are really demanding from a computational point of view.

To enhance accuracy, we need to estimate the ordinal grade variable, the first outcome defined, using BUC estimator. However, we require a less strict econometric specification from a fixed effect viewpoint to ensure estimation.[11] Therefore, the econometric specification is as follows:

$$Ordinal\_DV_{iect} = \beta_0 + \beta_1 \cdot Crime^{MD}_{iect} + \mu_i + \gamma_w + \varepsilon_{iect} \tag{1}$$

where the dependent variable $Ordinal\_DV_{iect}$ denotes the ordinal grade obtained by student i in the final exam e in the course c at academic year t, $Crime^{MD}_{iect}$ defined as the number of crimes occurred within M meters of the student residence over the previous D days before each final exam, where $M \in \{20, 40, 60, 80, 100, 300\}$ meters and $D \in \{7, 15, 30\}$ days, μ_i are student fixed-effects, γ_w are week fixed-effects, and ε_{iect} is the error term clustered at the census tract level.

[10] We only observe their place of residence once, the one they provide to the university the first year (in the enrolling period) or in case they changed in any moment of the next enrolling periods (annually). Our main assumption is that students did not move to another place over the period 2007-2010. Nevertheless, we perform several robustness exercises to check whether this might bias our results or not (see Section 4.1 for more details).

[11] We perform a robustness analysis to assess whether the relaxation of these econometric requirements could provide less precise estimates and bias our results, see Table A.1 in Appendix A.

Estimates from the *BUC* estimator are not straightforward to interpret. We assess the sign of the coefficients, their statistical significance and compare magnitudes without interpreting the specific magnitude of coefficients. We further deepen this analysis by estimating the expected changes in the probability of moving out from each category. Therefore, we obtain a better understanding of how crime influences the probability of students transitioning between grade categories. The estimation of expected changes in the probability allows us to assess both the magnitude and direction of these shifts.

Since the other outcomes analysed (dummy taking the final exam, dummy pass and dummy excellent) are dichotomic variables, a linear estimator can be used to estimate the econometric specification, and, thus, a more demanding specification can be performed. In this line, a more restrictive model is proposed with the time FE defined as exam FE, instead of week FE, and adding spatial trends FE, such as district-month FE. Concretely, the three-way student, exam and district-month fixed-effects panel data (HDFE) is defined as follows:

$$Binary\_DV_{iect} = \alpha_0 + \alpha_1 \cdot Crime^{MD}_{iect} + \mu_i + \theta_e + \tau_{dm} + \epsilon_{iect} \quad (2)$$

where the dependent variable $Binary\_DV_{iect}$ denotes the dichotomic dependent variable by student i in the final exam e in the course c at academic year t, $Crime^{MD}_{iect}$ defined as the number of crimes occurred within M meters of the student residence over the previous D days before each final exam, where $M \in \{20, 40, 60, 80, 100, 300\}$ meters and $D \in \{7, 15, 30\}$ days, μ_i are student fixed-effects, θ_e are exam fixed-effects, τ_{dm} spatial-time trends, concretely, district-month fixed-effects, and ϵ_{iect} is the error term clustered at the census tract level.

4.1 Potential threats to the identification strategy

The main challenges of the empirical strategy is to overcome the potential student selection into examinations, the potential endogeneity of the place where students live and time-variant unobserved variables, such as socioeconomic level, that might be correlated with student performance and crime exposure.

Selection into examinations

Exposure to crime might lead students not to sit an exam. This fact does not threaten our estimates as long as these students are randomly distributed according to ability. However, if not sitting an exam due to being exposed to crime is correlated with student ability, our estimates might be biased because of self-selection. For this reason, we analyse this potential threat by estimating Eq. (2) with a dummy dependent variable defined as sitting the exam or not. By doing so, we can observe whether exposure to crime influences the likelihood of attending the exam across different ability levels. Therefore, this analysis helps assessing whether our estimates are driven by an unobserved selection effect or not. This approach provides additional confidence in the reliability of our results and allows us to control for any systematic patterns of non-attendance related to crime exposure.

Residential sorting

One relevant concern in analysing the causal impact of crime on educational outcomes is the endogeneity of the place where students live. The family's decision on where to live, normally non-random, might determine student performance and the level of exposure to crime simultaneously. For example, a body of research has shown that low-socioeconomic neighbourhoods concentrate higher crime rates than high-socioeconomic neighbourhoods (see, for example, Krivo and Peterson, 1996; Chiu and Madden, 1998; Fajnzylber et al., 2002). At the same time, other studies have detected that the family's socioeconomic status is related to educational outcomes (see, for example, Dahl and Lochner, 2012; Bastian and Michelmore, 2018; OCDE, 2023). Our empirical strategy overcomes this potential threat by including student FE. By adding student FE, we get rid of any variation between students and, thus, any variation between the socioeconomic level of the place where they live. Therefore, our identification strategy relies on changes in the crime level within students over time and not between students.

Local changes over time

Student FE control for each student's time-invariant characteristics and neighbourhood characteristics. However, time-variant characteristics might be correlated with student performance and crime level. For this reason, we add spatial trends FE, concretely district-month FE, to control for local patterns over time. In this case, the spatial and time units are relevant and not straightforward, not only for the economic significance of our model but also for the statistical power. Adding more independent variables or FE into a model reduces its statistical power with a higher probability of Type II error. Moreover, defining spatial and time units more desegregated reduces our statistical power considerably. For this reason, given our setting, there is a trade-off between very precise spatial trends FE (more accurate, but with less statistical power) and less precise spatial trends FE (less accurate, but with more statistical power). We, thus, decide that district-month FE is an optimal balance. Additionally, we cluster standard errors at the census tract level to account for any within-census serial correlation in crime over time.

Measurement error in addresses

Two potential issues with the address data may challenge our empirical strategy: the potential inaccuracy of the reported addresses and the possibility that students may change residences during the period under study. To address these concerns, we perform two robustness exercises. First, we re-estimate our main analysis using a subsample of students born in the MAB – our main sample is formed by students living around the MAB –. These students are more likely to have stable and long-term addresses because they probably lived with their parents (the average age of emancipation was around 29 years in 2013 in Spain (Eurostat, 2024)). Since the average student age in our sample is 23, it's reasonable to infer that a significant portion of MAB-born students still live at their family home, making address data for this group more accurate and less susceptible to error from temporary relocations, short-term housing arrangements or movements from student housing. Second, we simulate potential address inaccuracies by randomizing a new location for each student in the sample and then re-estimate the impact of crime exposure at these randomized locations on student performance. This test helps verifying whether our findings are driven by the specific address data used.

5 Results

5.1 Main results

Table 6 shows the results obtained by estimating Eq. (1) for both violent and non-violent crimes within a distance of $M \in \{20, 40, 60, 80, 100, 300\}$ meters from the students' homes during the previous $D \in \{7, 15, 30\}$ days before each final exam. Each estimate corresponds to a distinct regression analysis.[12]

Coefficients show statistically significant negative effects for violent crimes in an area of radius 20 meters around students' homes, suggesting a detrimental impact on student grades over the three time periods analysed (7, 15, and 30 days before each final exam). Similarly, the results indicate statistically significant negative effects when considering a proximity of 60 meters within the 15-day and 30-day periods before an exam. Conversely, non-violent crimes exhibit less pronounced and statistically non-significant impacts on student performance across the specified distances and time intervals. Violent crimes show a suggestive pattern of diminishing impact as the distance from the student's residence increases and the number of days before the final exam increases. Extending the radius, we incorporate crime events from greater distances from homes, which may exhibit a lower impact than those closer. Similarly, extending the time frame to include more days before the final exam follows a comparable interpretation.[13]

[12] We conduct a robustness analysis to assess whether the relaxation of the econometric requirements explained in Section 4 could result in less precise estimates. To achieve this, we estimate Eq. (1) using the linear HDFE estimator provided by the REGHDFE Stata package, as well as a simpler specification to the one used in the OLPD estimates, also implemented with the same package. The results, detailed in Table A.1 in Appendix A, indicate that estimates for violent crime remain consistent between the full specification and the simpler version. Furthermore, comparing the logit estimates obtained from the linear HDFE estimator reveals a similarity between the two approaches. These findings enhance the robustness of our results across different econometric specifications, affirming the reliability of our analysis.

[13] We conduct sensitivity analyses by adjusting the categorization of violent and non-violent crimes. In our primary classification, violent crimes include robbery, injuries, threats, gender- and sexual-based violence, family-related offences, murder, and other crimes against individuals (see Table 3). Nevertheless, certain types of crimes, such as robbery or family-related offences, may involve little or no violence. On the one hand, we re-estimate the primary analysis by excluding robbery from the violent crime category and reclassifying it as non-violent. Table A.2 in Appendix A shows similar results to those of this Table 6. On the other hand, we perform the same previous analysis but now exclude family crimes from the violent crime category and reclassify them as non-violent. Table A.3 in Appendix A shows similar results to those in Table 6.

Table 6: Impact of violent and non-violent crimes on the probability of a higher ordinal grade

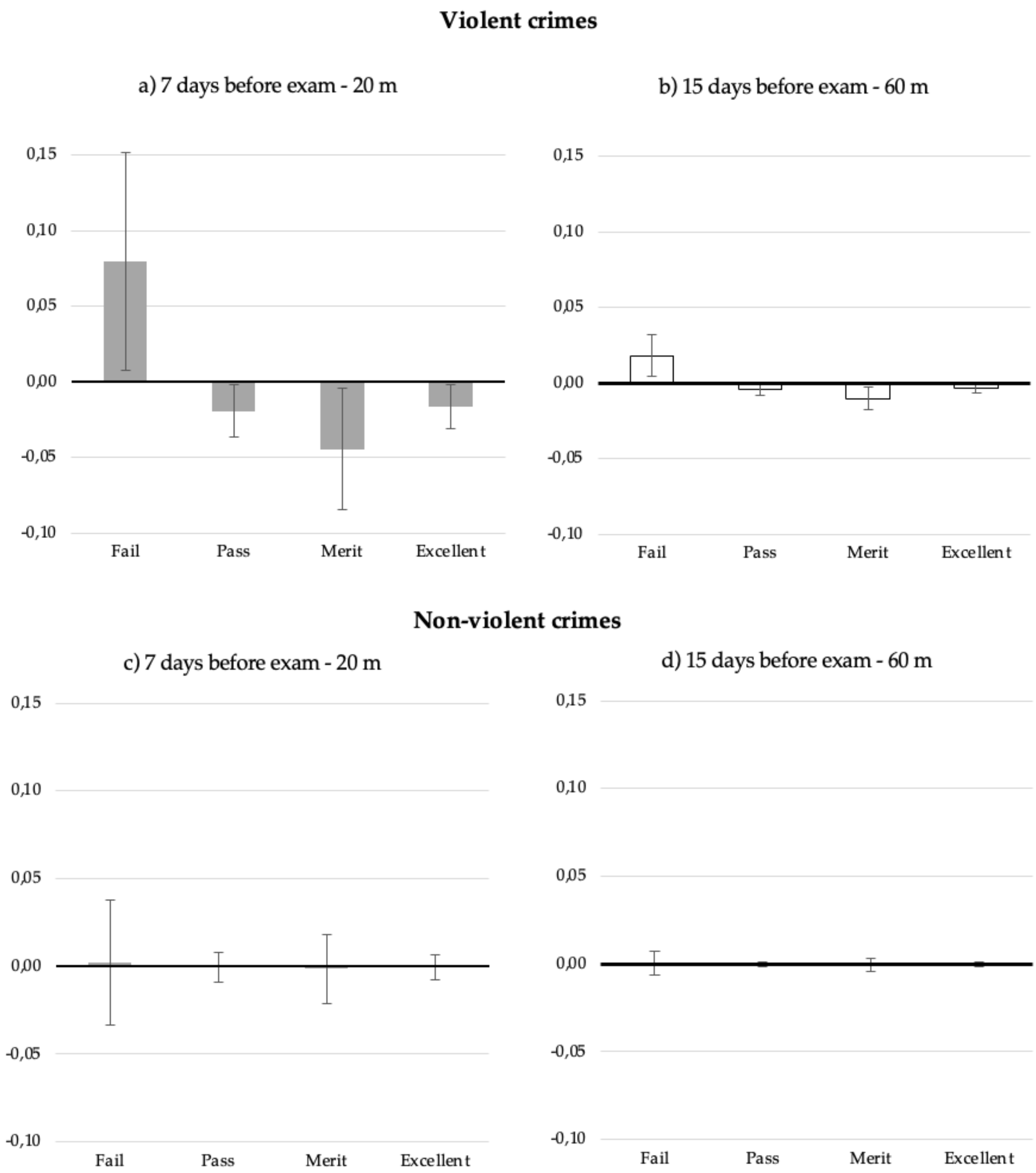
	(1)	(2)	(3)	(4)	(5)	(6)
	Violent crime			Non-violent crime		
	7 days	15 days	30 days	7 days	15 days	30 days
20 m.	-0.340**	-0.304***	-0.137**	-0.009	0.037	0.019
	(0.156)	(0.091)	(0.065)	(0.076)	(0.056)	(0.037)
40 m.	0.016	-0.045	-0.035	0.005	0.015	0.010
	(0.066)	(0.046)	(0.033)	(0.034)	(0.023)	(0.017)
60 m.	-0.047	-0.077**	-0.037*	-0.006	-0.001	-0.002
	(0.042)	(0.030)	(0.021)	(0.022)	(0.014)	(0.010)
80 m.	-0.016	-0.026	-0.011	0.008	-0.004	-0.007
	(0.032)	(0.023)	(0.016)	(0.017)	(0.011)	(0.006)
100 m.	-0.019	-0.025	-0.012	0.006	0.002	-0.001
	(0.027)	(0.019)	(0.013)	(0.008)	(0.004)	(0.003)
300 m.	-0.003	-0.001	-0.001	0.003	0.002	0.000
	(0.008)	(0.006)	(0.004)	(0.003)	(0.001)	(0.001)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes

Observations: 18,755 student-exams pairs (712 unique students) for each estimate. Notes: each of these estimates comes from a separate estimation of Eq. (1 using *BUC* estimator (see Section 4 for more details). The ordinal dependent variable – grades – might take four possible values: fail, pass, merit and excellent. Each independent variable of interest – number of crimes – has been computed as the number of crimes that occurred within $X \in \{20, 40, 60, 80, 100, 300\}$ meters from their residence over the previous $D \in \{7, 15, 30\}$ days of each final exam taken by the students. Standard errors clustered at the census tract level are in parentheses, and *** denotes significance at the 1% level, ** the 5% level and * the 10% level.

As stated in Section 4, estimates from Table 6 are difficult to interpret since they are expressed in a log-odds scale. For this reason, we examine the expected change in the predicted probability of each ordinal grade value. This is how the predicted probability of obtaining a specific grade changes when a unit-increase crime occurs near students' residences. Figure 3 shows the results of this exercise for two specific cases: when analysing 20 metres 7 days before the final exam and 60 metres 15 days before the final exam. Both cases show that the probability of failing increases while the probability of getting one of the other's grades decreases. Concretely, the probability of failing the exam increases by 8.0 p.p. for each additional crime at 20 metres over the previous 7 days, while the probability of getting a pass decreases by 1.9 p.p., getting a merit of 4.4 p.p. and getting an excellent by 1.6 p.p. Note that panel b shows a reduction in the magnitude of the effect since the larger radius and time windows. Therefore, violent crime near students' homes increases the probability of failing a final exam, and the magnitude diminishes as distances and/or days increase.

To assess the magnitude of these impacts, Table 2 shows the distribution of the ordinal grade outcome. Out of 18,821 student-exams pairs, 37.7% failed an exam, 39.2% obtained a pass grade, 18.1% received a merit, and 5% an excellent. The impact of 8.0 p.p. (20 metres and 7 days) is translated into 1,506 additional students failing an exam (student-exam pair) over their university studies due to crime exposure and 301 students not achieving an excellent. In contrast, the impact of 1.8 p.p. (60 metres and 15 days) is translated into 339 more students failing and the reduced probability of obtaining an excellent grade in 75 fewer student-exam pair.

Figure 3: Impact of crimes on the probability of getting each of the ordinal grades categories



Observations: see Table 6. Notes: estimates from Table 6 are decomposed for each ordinal grade category.

To analyse gender-specific patterns, we divide the sample into female and male students and re-estimate Eq. (1) for each subsample. Table 7 indicates that the negative impact of crime on student performance is mainly observed among male students. Logically, the point estimates are higher than those observed in Table 6 since these are averages among female students (no impact) and male students (negative effect). Despite this, estimates from the subsample of female students also show spatial and temporary patterns: the magnitude of the point estimates decreases with larger buffers and time periods before final exams. As shown in Table (6), the estimates for non-violent crimes are not statistically significant.

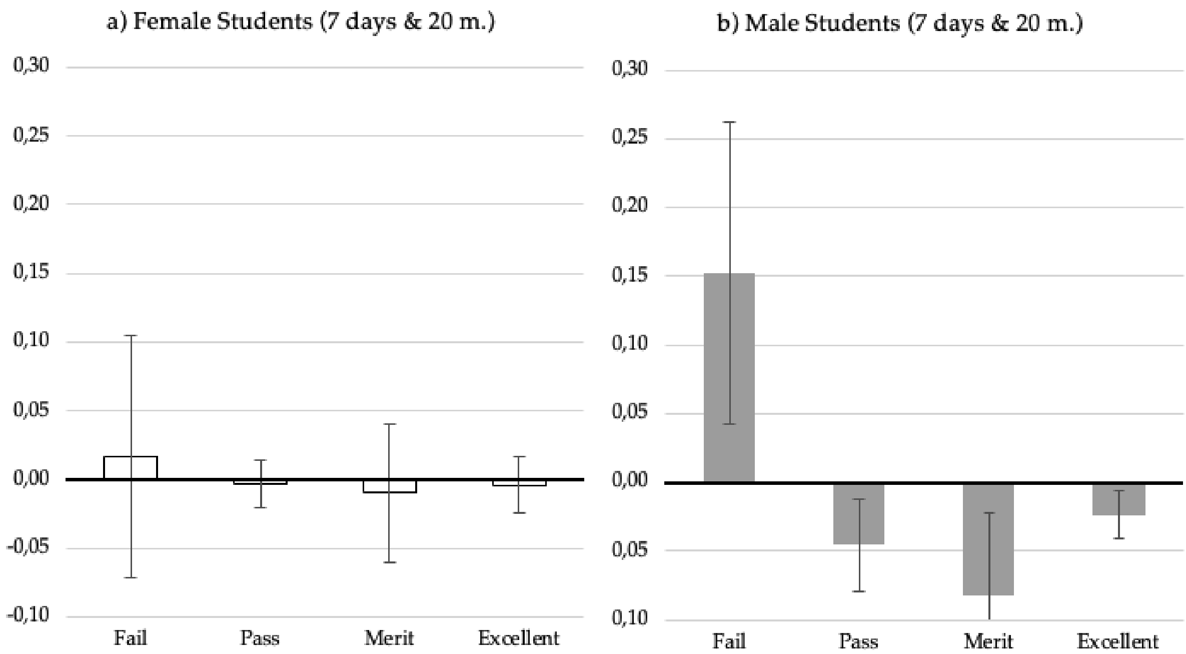
Table 7: Impact of violent crimes on the probability of a higher ordinal grade by gender

	(1)	(2)	(3)	(4)	(5)	(6)
	Female students			Male students		
	7 days	15 days	30 days	7 days	15 days	30 days
20 m.	-0.072	-0.126	-0.031	-0.642***	-0.506***	-0.278***
	(0.194)	(0.114)	(0.085)	(0.238)	(0.138)	(0.092)
40 m.	0.039	0.015	-0.030	-0.006	-0.110	-0.044
	(0.087)	(0.063)	(0.049)	(0.101)	(0.068)	(0.044)
60 m.	-0.068	-0.051	-0.048	-0.027	-0.117**	-0.029
	(0.058)	(0.039)	(0.030)	(0.061)	(0.047)	(0.031)
80 m.	-0.028	-0.008	-0.014	-0.009	-0.059*	-0.012
	(0.044)	(0.030)	(0.021)	(0.046)	(0.036)	(0.025)
100 m.	-0.023	-0.014	-0.012	-0.022	-0.049	-0.018
	(0.039)	(0.025)	(0.018)	(0.041)	(0.031)	(0.020)
300 m.	-0.003	-0.001	-0.001	-0.006	-0.005	-0.005
	(0.012)	(0.009)	(0.006)	(0.014)	(0.010)	(0.007)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes

Observations: 10,590 female student-exams pairs (395 unique students) for each estimate in columns (1)-(3) and 8,165 male student-exams pairs (317 unique students) for each estimate in columns (4)-(6). Notes: see notes in Table 6.

We also perform the same exercise as in Figure 3, but with a gender perspective. Figure 4 shows the results of male and female students for the case of the number of violent crimes that occurred around 20 metres over the seven days before final exams. Comparing the two panels from Figure 4, we observe the same patterns as before: an increase of one unit of crime near their residence leads to a rise in the probability of failing the exam. In contrast, the probability of achieving any of the other grades decreases. However, in this case, the expected average changes in the probability are larger in magnitude for male students than for female students. Moreover, the coefficients are not statistically significant for female students.

Figure 4: Impact of violent crimes on the probability of getting each of the ordinal grade categories by gender



Observations: see Table 7. Notes: estimates from Table 7 are decomposed for each ordinal grade category.

5.1.1 Selection into examination

The results presented so far might be affected by selection bias due to the influence of exposure to crime on the probability of taking final exams. To address this issue, we analyse the probability of sitting for the final exam. Examining the potential impact of local crime on this variable allows us to explore the relationship between crime and academic performance more deeply. Table 8 indicates no significant impact of local crime on the probability of taking final exams. We also analyse by gender, and the results remain consistent (see Table A.4 in Appendix A). Thus, we confirm that the number of crimes near students' residences before final exams does not influence their decision to take them. Consequently, we conclude that our previous findings are robust and not biased by any selection associated with students' decisions to take their final exams.

Table 8: Impact of violent and non-violent crimes on the probability of sitting a final exam

	(1)	(2)	(3)	(4)	(5)	(6)
	Violent crime			Non-violent crime		
	7 days	15 days	30 days	7 days	15 days	30 days
20 m.	-0.034	-0.020	0.004	0.004	0.005	0.008
	(0.024)	(0.016)	(0.013)	(0.011)	(0.008)	(0.006)
40 m.	-0.000	0.007	0.007	-0.001	-0.005	0.002
	(0.010)	(0.007)	(0.005)	(0.005)	(0.004)	(0.002)
60 m.	-0.011	0.001	0.003	-0.002	-0.001	0.001
	(0.007)	(0.005)	(0.004)	(0.004)	(0.003)	(0.002)
80 m.	-0.003	0.002	0.003	-0.001	-0.000	0.000
	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.001)
100 m.	0.006	0.004	0.004	0.001	0.000	0.000
	(0.004)	(0.003)	(0.002)	(0.002)	(0.001)	(0.000)
300 m.	-0.001	0.000	0.001	0.001	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam FE	Yes	Yes	Yes	Yes	Yes	Yes
District-month FE	Yes	Yes	Yes	Yes	Yes	Yes

Observations: 24,313 student-exams pairs (749 unique students) for each estimate. Notes: each of these estimates comes from a separate estimation of Eq. (2 using REGHDFE Stata package (see Section 4 for more details). The dichotomic dependent variable takes a value of 1 if the student sat the final exam and 0 otherwise (no-show). The independent variable of interest – number of crimes – has been computed as the number of crimes that occurred within $X \in \{20, 40, 60, 80, 100, 300\}$ meters from their residence over the previous $D \in \{7, 15, 30\}$ days of each final exam taken by the students. Standard errors clustered at the census tract level are in parentheses, and *** denotes significance at the 1% level, ** the 5% level and * the 10% level.

5.1.2 Probability to pass and to excel

Table 9 shows the impact of violent crime exposure on our other two binary outcomes: the probability of passing the final exam and the probability of obtaining an excellent grade. As discussed in Section 4, since these dependent variables are dichotomic, we estimate the full specification (Eq. 2), which includes a highly restrictive set of fixed effects: student, exam, and spatial trends.The results for the pass outcome confirm previous findings presented in Table 6 and Figure 3: students exposed to violent crime within 20 metres of their residence in the 15 days before the exam are significantly less likely to pass. The estimated effect is a 7.5 p.p. reduction in the probability of passing for a one-unit increase in violent crime around 20 metres in the previous 7 days, which is consistent with the 8 p.p. increase in the probability of failing reported in Figure 3.

The results for the excellent outcome indicate a significant and consistent negative impact of violent crimes on the probability of achieving an excellent grade, specifically when taking into account violent crimes that occurred over 7 and 15 days before final exams. For instance, the coefficient of -0.012 at 40 meters (15 days before the exam) implies that a one-unit increase in violent crimes leads to a statistically significant decrease in the probability of obtaining an excellent grade by 1.2 p.p. As shown in Table 2, only 5% of students obtained an excellent grade over the academic years. Therefore, an expected change of 1.2 p.p. is significant and implies that 225 students do not achieve excellent grades due to exposure to violent crime near their residences.[14]

Table 9: Impact of violent crimes on the probability of passing and obtaining an excellent

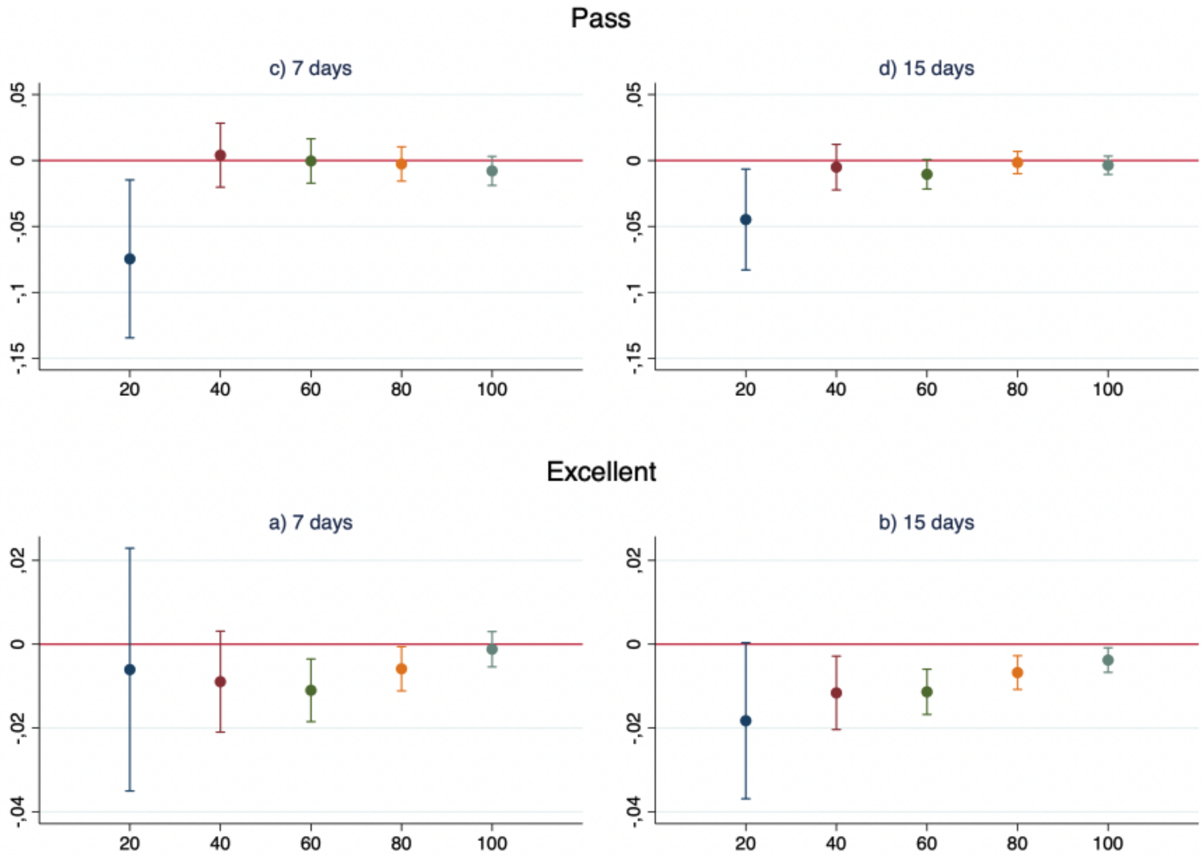
	(1)	(2)	(3)	(4)	(5)	(6)
	Pass Dummy			Excellent Dummy		
	7 days	15 days	30 days	7 days	15 days	30 days
20 m.	-0.075**	-0.045*	-0.027*	-0.006	-0.018	-0.009
	(0.036)	(0.023)	(0.015)	(0.018)	(0.011)	(0.007)
40 m.	0.004	-0.005	-0.010	-0.009	-0.012**	-0.001
	(0.015)	(0.010)	(0.007)	(0.007)	(0.005)	(0.004)
60 m.	-0.000	-0.010	-0.008	-0.011**	-0.011***	-0.004
	(0.010)	(0.007)	(0.005)	(0.005)	(0.003)	(0.002)
80 m.	-0.003	-0.002	-0.005	-0.006*	-0.007***	-0.001
	(0.008)	(0.005)	(0.004)	(0.003)	(0.002)	(0.002)
100 m.	-0.008	-0.004	-0.004	-0.001	-0.004**	-0.001
	(0.007)	(0.004)	(0.003)	(0.003)	(0.002)	(0.001)
300 m.	-0.003*	-0.001	-0.001	0.001	0.000	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam FE	Yes	Yes	Yes	Yes	Yes	Yes
District-month FE	Yes	Yes	Yes	Yes	Yes	Yes

Observations: 18,678 student-exams pairs (721 unique students) and 143 singleton observations dropped for each estimate. Notes: each of these estimates comes from a separate estimation of Eq. (2) using REGHDFE Stata package (see Section 4 for more details). The dichotomic dependent variable takes a value of 1 if the student obtained an excellent or an excellent with honours on the final exam and 0 otherwise (no-show is coded as missing value). The independent variable of interest – number of crimes – has been computed as the number of crimes that occurred within $X \in \{20, 40, 60, 80, 100, 300\}$ meters from their residence over the previous $D \in \{7, 15, 30\}$ days of each final exam taken by the students. Standard errors clustered at the census tract level are in parentheses, and *** denotes significance at the 1% level, ** the 5% level and * the 10% level.

Figure 5 shows the estimates from columns (1), (2), (4) and (5) of Table 9, i.e. the impact of violent crimes over the previous 7 and 15 days before final exams. This figure helps us to understand how the negative impact decreases as we increase the buffer in the case of the probability of obtaining an excellent result. We hypothesise that by increasing the buffer, we include more crimes that occurred further away from students' residences. As a result, the impact of each crime diminishes until it is totally diluted by further crimes with lower or no potential impact.

[14] Similar findings are observed when excluding *merit* and *excellent* grades from the pass outcome and when excluding *fail* and *pass* grades from the excellent outcome (see Table A.5 in Appendix A). The persistence of similar estimates after excluding grade categories suggests, on the one hand, that the impact on passing the final exams is targeted at students failing or getting a pass grade, i.e., bottom-performing students. On the other hand, the impact on excellent grades is targeted at students achieving merit and excellent grades, i.e., top-performing students.

Figure 5: Impact of violent crimes over the previous 7 and 15 days of final exams on the probability of passing and obtaining an excellent, graphical representation



Observations: see Table 9. Notes: see notes in Table 9. The vertical axes have different scales.

We next analyse whether the impact of violent crimes near students' residences on the probability to pass the exam or on the excellent dummy outcome differs by gender. Table 10 indicates that the results on the probability of passing the exam come from male students, while female students are those more affected by violent crimes when trying to obtain higher grades (far less pronounced by males). This latter effect for females is more prominent at shorter buffers, i.e., 20, 40, and 60 meters. Note that as we increased the buffer ring, the magnitude of the point estimate diminishes. Specifically, the magnitude ranges between 3 p.p. (20 metres) and 0.9 p.p. (60 metres) for the excellent dummy and between 6 p.p. (20 metres) and 2 p.p. (60 metres) for the pass dummy outcome.

Table 10: Impact of violent crimes on the probability of passing and obtaining an excellent grade by gender over 15 days

	(1)	(2)	(3)	(4)
	Pass Dummy		Excellent Dummy	
	Female	Male	Female	Male
20 m.	-0.007	-0.062*	-0.031**	-0.004
	(0.032)	(0.036)	(0.015)	(0.016)
40 m.	0.012	-0.023	-0.015**	-0.001
	(0.015)	(0.016)	(0.007)	(0.007)
60 m.	-0.002	-0.019*	-0.010**	-0.008*
	(0.009)	(0.010)	(0.005)	(0.005)
80 m.	0.004	-0.009	-0.005	-0.006*
	(0.007)	(0.008)	(0.004)	(0.003)
100 m.	0.001	-0.008	-0.002	-0.003
	(0.006)	(0.007)	(0.003)	(0.003)
300 m.	-0.003	-0.000	0.001	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Student FE	Yes	Yes	Yes	Yes
Exam FE	Yes	Yes	Yes	Yes
District-month FE	Yes	Yes	Yes	Yes

Observations: 10,455 female student-exams pairs (396 unique students) and 144 singleton observations dropped for each estimate in columns (1) and (3). 8,091 male student-exams pairs (325 unique students) and 131 singleton observations dropped for each estimate in columns (2) and (4). Notes: see notes in Table 9.

These results help to deepen our understanding of the findings related to ordinal grade outcome: violent crimes negatively affect student performance, but their impact differs by gender. While male students are more likely to be affected in terms of failing final exams, female students are more impacted in their probability of obtaining excellent grades. This suggests that violent crime primarily affects male students at the lower end of the grade distribution, and female students at the upper end.

5.2 Heterogeneity analysis

5.2.1 Results by student ability

This subsection examines how the impact of violent crimes on student performance varies according to students' abilities. We use the bachelor's final GPA as a proxy for students' ability.[15] We classify students into two groups based on their GPA: high-ability and low-ability. The threshold for this classification is the median GPA of the sample, which is 1.3, identical to the mean. Accordingly, students with a GPA of 1.3 or lower are categorised as low-ability, while

[15]While one might argue that these grades are endogenous to the events under study, we clarify that it is not used as an independent variable in our models. Instead, we use it only to proxy students' abilities. An alternative measure could be the grade of the university exam entrance to the Bachelor's degree. However, there are different university entry paths, with different evaluation systems. Moreover, we do not observe the entry grade for a proportion of students.

those with a GPA above 1.3 are considered high-ability. On a numerical scale ranging from 0 to 10, a GPA of 1.3 corresponds to a grade of 5.6, which is equivalent to the *pass* grade on the ordinal grading scale. This heterogeneity analysis seeks to analyse whether high-ability and low-ability students are equally affected by their exposure to crime and whether gender differences vary according to their ability.

Table 11 shows the distribution of the GPA of the students in our sample. Most of the students, 63.7 %, have a GPA between 1.1 and 1.3 (out of 4), and the distribution varies by gender. Female students are more present in the higher part of the GPA distribution, with 2.6% of them having a GPA of 2.0 or more compared to 0.9% of male students. Interestingly, there is a higher proportion of male students (26.1%) with the lowest GPA (1.0 and 1.1) compared to female students (13.4%). Overall, the table suggests that female students tend to achieve higher GPA than their male counterparts in their bachelor's studies.

Table 11: Average GPA Distribution by gender

	All students		Female students		Male students	
GPA	Frequency	%	Frequency	%	Frequency	%
1.0	37	4.9	14	3.4	23	6.8
1.1	106	14.2	41	10.0	65	19.3
1.2	181	24.2	100	24.3	81	24.0
1.3	189	25.3	112	27.2	77	22.8
1.4	102	13.6	63	15.3	39	11.6
1.5	51	6.8	26	6.3	25	7.4
1.6	35	4.7	23	5.6	12	3.6
1.7	16	2.1	11	2.7	5	1.5
1.8	12	1.6	7	1.7	5	1.5
1.9	5	0.7	3	0.7	2	0.6
2.0	7	0.9	4	1.0	3	0.9
2.1	1	0.1	1	0.2	-	-
2.2	1	0.1	1	0.2	-	-
2.3	4	0.5	4	1.0	-	-
2.7	1	0.1	1	0.2	-	-

Notes: GPA might take values between 1 and 4, being 1 the lowest grade and 4 the highest grade.

Table 12 examines the heterogeneous effects of violent crime exposure within 15 days before final exams on students' ordinal grade outcomes, disaggregated by ability and gender. The negative and statistically significant coefficients at 20, 60 and 80 metres in column (1) suggest that high-ability students are more affected than their low-ability peers. These effects are primarily driven by high-ability male students, who experience a higher probability of lower ordinal grades. Nonetheless, low-ability male students show even larger negative effects at these distances compared to their high-ability counterparts. In contrast, there is no evidence that either high- or low-ability female students are affected by violent crime exposure when analysing the ordinal grade variable. These findings indicate that an increased number of crimes near the students' residences significantly impacts the performance of male students, especially low-ability students.

Table 12: Impact of violent crimes over 15 days previous to the final exam on the probability of a higher ordinal grade by ability and gender

	(1)	(2)	(3)	(4)	(5)	(6)
	All students		Female students		Male students	
	High-ability	Low-ability	High-ability	Low-ability	High-ability	Low-ability
20 m.	-0.306***	-0.329**	-0.237	-0.085	-0.395***	-0.632***
	(0.115)	(0.139)	(0.159)	(0.163)	(0.151)	(0.239)
40 m.	-0.070	-0.041	-0.072	0.060	-0.056	-0.145*
	(0.077)	(0.057)	(0.101)	(0.080)	(0.119)	(0.087)
60 m.	-0.132**	-0.050	-0.097*	-0.019	-0.170*	-0.087*
	(0.053)	(0.035)	(0.059)	(0.051)	(0.089)	(0.047)
80 m.	-0.071*	-0.006	-0.040	0.009	-0.134*	-0.019
	(0.039)	(0.027)	(0.043)	(0.040)	(0.069)	(0.036)
100 m.	-0.035	-0.026	-0.008	-0.026	-0.100	-0.027
	(0.035)	(0.022)	(0.037)	(0.033)	(0.064)	(0.031)
300 m.	-0.002	-0.002	-0.004	-0.002	-0.003	-0.005
	(0.012)	(0.007)	(0.015)	(0.010)	(0.020)	(0.010)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,176	12,579	3,941	6,649	2,235	5,930
Students	231	481	143	252	88	229

Notes: see notes in Table 6. High-ability and low-ability students are defined at the beginning of this Section 5.2.

We now perform the same analysis using our dummy educational outcomes. Table 13 shows that high-ability students exposed to violent crimes within a 20-meter radius of their residence experience a 6.7 percentage point reduction in their probability of passing the exam, statistically significant at the 5% level. When disaggregating by gender, the effect is shown to be driven primarily by high-ability female students, who experience a similarly sized and statistically significant decline of 8.2 percentage points. No statistically significant effects are observed for low-ability students or male students of either ability group. These results suggest that violent crime exposure at closer distances increases the probability of failing for high-ability female students.

Table 13: Impact of violent crimes over 15 days previous to the final exam on the probability of passing by ability and gender

	(1)	(2)	(3)	(4)	(5)	(6)
	All students		Female students		Male students	
	High-ability	Low-ability	High-ability	Low-ability	High-ability	Low-ability
20 m.	-0.067**	-0.039	-0.082**	0.042	-0.011	-0.078
	(0.026)	(0.036)	(0.039)	(0.043)	(0.035)	(0.056)
40 m.	-0.004	-0.009	-0.018	0.026	0.022	-0.037
	(0.016)	(0.015)	(0.024)	(0.019)	(0.028)	(0.023)
60 m.	-0.020	-0.007	-0.019	0.000	-0.016	-0.012
	(0.013)	(0.009)	(0.016)	(0.013)	(0.024)	(0.013)
80 m.	-0.008	0.001	-0.001	0.006	-0.018	0.001
	(0.010)	(0.006)	(0.011)	(0.010)	(0.022)	(0.009)
100 m.	-0.007	-0.002	-0.003	0.003	-0.018	-0.001
	(0.008)	(0.005)	(0.009)	(0.008)	(0.018)	(0.008)
300 m.	-0.000	-0.002	-0.003	-0.003	0.001	-0.000
	(0.003)	(0.002)	(0.003)	(0.002)	(0.005)	(0.003)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam FE	Yes	Yes	Yes	Yes	Yes	Yes
District-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,056	12,496	3.832	6,526	2,128	5,869
Students	231	490	142	253	88	236

Notes: see notes in Table 6. High-ability and low-ability students are defined at the beginning of this Section 5.2.

Table 14 presents the impact of violent crimes on the probability of obtaining an excellent grade on final exams by student ability and gender. As expected, the results indicate that high-ability students are negatively affected by violent crimes occurring within 40, 60, and 80 meters of their residence during the 15 days preceding the exam. Specifically, each additional violent crime is associated with a reduction in the probability of obtaining an excellent grade by 2.2, 1.9, and 1.3 p.p., respectively. Gender analysis indicates that the negative effects among high-ability students are primarily driven by females, while no statistically significant impact is observed for high-ability male students.

Table 14: Impact of violent crimes over 15 days previous final exam on the probability of obtaining an excellent by ability and gender

	(1)	(2)	(3)	(4)	(5)	(6)
	All students		Female students		Male students	
	High-ability	Low-ability	High-ability	Low-ability	High-ability	Low-ability
20 m.	-0.015	-0.012	-0.029	-0.018	-0.018	-0.013
	(0.026)	(0.009)	(0.031)	(0.014)	(0.028)	(0.012)
40 m.	-0.022*	-0.003	-0.040**	-0.002	-0.010	-0.003
	(0.013)	(0.004)	(0.019)	(0.006)	(0.014)	(0.006)
60 m.	-0.019**	-0.004*	-0.024**	-0.002	-0.016	-0.007*
	(0.008)	(0.003)	(0.012)	(0.004)	(0.013)	(0.004)
80 m.	-0.013**	-0.002	-0.016*	0.002	-0.010	-0.006*
	(0.006)	(0.002)	(0.008)	(0.003)	(0.009)	(0.003)
100 m.	-0.007	-0.001	-0.004	0.001	-0.005	-0.002
	(0.005)	(0.002)	(0.007)	(0.002)	(0.008)	(0.003)
300 m.	0.001	0.000	-0.000	0.000	0.004	-0.001
	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam FE	Yes	Yes	Yes	Yes	Yes	Yes
District-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,056	12,496	3.832	6,526	2,128	5,869
Students	231	490	142	253	88	236

Notes: see notes in Table 6. High-ability and low-ability students are defined at the beginning of this Section 5.2.

Overall, these findings suggest that, in general, high-ability students are more negatively affected by exposure to violent crime than their low-ability counterparts. This pattern holds consistently across different educational outcomes. Moreover, our results indicate the existence of gender differences in how crime exposure impacts student performance depending on students' ability. For the ordinal grade outcome, and consistently with results shown in Table (7), the negative effects are driven by both high- and low-ability male students, albeit slightly more pronounced for the latter. In contrast, we observe a negative impact on both the probability of passing the exam and, especially, on the probability of obtaining an excellent grade for high-ability female students.

5.2.2 Results by detailed crime categories

This subsection explores the effects of specific crime categories to deepen the analysis of how exposure to violent crime impacts student performance. While we have broadly differentiated between violent and non-violent crimes, Table 3 shows that crimes can be further divided into more detailed categories. Analysing these categories may help uncover the underlying mechanisms that drive our main results. However, disaggregating crimes by detailed categories substantially reduces occurrence rates. Therefore, we focus on a selected set of crime categories based on the degree of victimisation by gender and a minimum occurrence threshold.[16]

Table 15 presents the effects of exposure to threats and sexual and gender violence on academic outcomes for female students. The results indicate that sexual and gender-based violence has a consistent and significant negative impact on the probability of achieving an excellent grade, with effects observed from 20 to 80 meters. For instance, at 40 meters, exposure to such crimes is associated with a 5.6 percentage point decrease, significant at the 1% level. In contrast, the effect on ordinal grades is only marginally significant at 20 meters, and there is no significant impact on the probability of passing. Regarding threats, we find statistically significant negative effects on both the probability of passing and obtaining an excellent grade at 20 and 40 meters, with the strongest effect at 20 meters. These findings suggest that female students' performance, particularly at the top of the grade distribution, is adversely affected by exposure to threats and gender-based violence near their homes.

Table 15: Educational impacts of different crime categories over the 15 days before final exams for female students

	(1)	(2)	(3)	(4)	(5)	(6)
	Ordinal Grade		Pass Dummy		Excellent Dummy	
	Threats	Sex. & gender violence	Threats	Sex. & gender violence	Threats	Sex. & gender violence
20 m.	-0.531	-0.512**	-0.136***	-0.078	-0.101***	-0.057**
	(0.412)	(0.242)	(0.050)	(0.053)	(0.037)	(0.024)
40 m.	-0.369	0.016	-0.034	0.040	-0.052**	-0.056***
	(0.242)	(0.146)	(0.048)	(0.034)	(0.025)	(0.016)
60 m.	0.028	-0.141	0.001	-0.010	-0.017	-0.038***
	(0.140)	(0.134)	(0.026)	(0.024)	(0.015)	(0.012)
80 m.	0.028	-0.108	-0.000	0.000	-0.005	-0.017*
	(0.113)	(0.094)	(0.023)	(0.018)	(0.012)	(0.009)
100 m.	0.002	-0.077	-0.001	0.007	-0.002	-0.007
	(0.089)	(0.068)	(0.018)	(0.013)	(0.010)	(0.007)
300 m.	0.004	0.005	0.001	0.002	0.000	-0.003
	(0.025)	(0.023)	(0.006)	(0.005)	(0.003)	(0.003)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam FE	No	No	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	No	No	No	No
District-month FE	No	No	Yes	Yes	Yes	Yes

Observations: 10,590 female student-exams pairs (395 unique students) for the ordinal grade estimates and 10,455 female student-exams pairs (396 unique students) for the pass and excellent dummies estimates. Notes: see notes in Table 6.

Table 16 reports the impact of injuries and robberies on academic performance among male students. Exposure to injury-related crimes is associated with a significant reduction in ordinal grade outcomes at all distances up to 100 meters, with the largest effect observed at 20 meters.

[16] Table 4 indicates that females are more frequently victims of sexual and gender-based violence and threats. In contrast, males are more frequently targeted by physical aggression, including injuries and robbery. As shown in Table 3, detailed crime categories with extremely low incidence may lack sufficient variation for reliable estimations.

Robbery only negatively affects ordinal grade performance when considering incidents at 20 metres from students' residences. While we do not observe effects on the probability of passing, injury crimes have small but significant impacts on the probability of obtaining an excellent grade at 80 meters, and robbery shows marginal effects at both 60 and 80 meters. These results suggest that male students' academic performance is particularly sensitive to violent crime involving physical harm, even at mid-range distances.

Table 16: Educational impact of different crime categories over the 15 days before final exams for male students

	(1)	(2)	(3)	(4)	(5)	(6)
	Ordinal Grade		Pass Dummy		Excellent Dummy	
	Injuries	Robbery	Injuries	Robbery	Injuries	Robbery
20 m.	-0.937*	-0.396**	-0.007	-0.069	-0.011	-0.003
	(0.504)	(0.173)	(0.103)	(0.044)	(0.023)	(0.021)
40 m.	-0.365**	-0.101	-0.004	-0.026	-0.013	-0.005
	(0.177)	(0.089)	(0.046)	(0.021)	(0.019)	(0.008)
60 m.	-0.422***	-0.057	-0.041	-0.011	-0.014	-0.011*
	(0.132)	(0.055)	(0.036)	(0.013)	(0.010)	(0.006)
80 m.	-0.231**	-0.011	-0.020	-0.003	-0.013*	-0.008*
	(0.100)	(0.042)	(0.024)	(0.010)	(0.007)	(0.004)
100 m.	-0.159**	0.001	-0.023	-0.001	-0.008	-0.004
	(0.077)	(0.037)	(0.020)	(0.009)	(0.006)	(0.004)
300 m.	-0.037	-0.015	-0.002	0.001	-0.001	0.000
	(0.026)	(0.012)	(0.007)	(0.003)	(0.002)	(0.001)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam FE	No	No	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	No	No	No	No
District-month FE	No	No	Yes	Yes	Yes	Yes

Observations: 8,165 male student-exams pairs (317 unique students) for the ordinal grade estimates and 8,091 female student-exams pairs (325 unique students) for the pass and excellent dummies estimates. Notes: see notes in Table 6.

5.3 Placebo tests

This subsection seeks to strengthen the validity of our findings and address potential sources of bias. Thus, we offer greater confidence and robustness in the causal interpretation of our results. We employ three placebo tests to ensure that the observed effects are explicitly driven by exposure to crime around students' residences rather than by unobserved factors or spurious correlations. Moreover, we test whether potential measurement errors in addresses might drive our results.

We first perform a placebo test by randomly assigning each student in our main sample to a new address from within the MAB. This random reassignment should eliminate any systematic relationship between crime exposure at the fictitious address and students' academic outcomes. Results, presented in Table A.6 in Appendix A, generally show no consistent or meaningful impact of either violent or non-violent crimes on the ordinal grade outcome or the excellent dummy outcome across most distances and periods. While a very few coefficients are statistically significant — some even positive — they do not follow a clear pattern across distances or time-frames, suggesting they are likely due to random variation rather than a systematic relationship. This lack of consistent findings in the placebo tests supports the validity of our main results, indicating that the potential measurement error of addresses does not affect our main results.[17]

We then examine whether future crime events might spuriously appear to influence exam performance. This analysis addresses any concerns that the effects of crime exposure might not be specifically tied to the period leading up to exams but could reflect general environmental factors or psychological stressors unrelated to exam preparation, providing an additional layer of validation of our causal estimates. Thus, each final exam date is shifted exactly one year later, recalculating crime variables based on these new dates. The central hypothesis is that estimates should not show any relation between crime variable and student performance since future crimes cannot affect previous student performance and, at the same time, student performance cannot influence the number of crimes committed around students' homes. Table A.8 in Appendix A indicate no consistent significant effects of either violent or non-violent crimes across distances and time periods for the ordinal grade and excellent dummy outcomes. Moreover, coefficients show no coherent pattern across distances or timeframes, with signs alternating between positive and negative.

We finally assign a completely random date to each exam and recompute the number of crimes according to the new dates. The underlying hypothesis for this test is similar: there should be no systematic relationship between crime exposure and academic outcomes when the exam dates are randomly assigned, as this setup eliminates any temporal link between crime events and exam performance. Results, found in Table A.9 in Appendix A, similarly show no consistent significant effects, with coefficients again lacking any coherent pattern and signs alternating between positive and negative. These findings further confirm that the observed effects in the main analysis are specific to the actual period before exams and are unlikely to result from random or confounding factors.

6 Discussion and conclusion

This paper has examined the impact of exposure to crime on university student performance, focusing on potential gender differences. We combined geocoded data of crimes committed in the MAB with academic and socio-demographic information from a sample of the BBA of the University of Barcelona. By following these students over four academic years and exploiting super-local crime variations during their final exams, we employed a three-way fixed-effect panel data approach with student, exam, and spatial trends fixed-effects to mitigate potential

[17] We perform a second sensitivity analysis to address potential inaccuracies in address data and possible residential changes during the period analysed. We focus on those students who were born in the MAB area. Our main hypothesis is that students born locally are more likely to have stable, accurate address data, which strengthens the reliability of spatial measures and reduces potential bias from factors such as transitory student populations or address mismatches. Table A.7 in Appendix A show the findings for the main types of crimes, examining both the ordinal grade outcome and the excellent dummy outcome. Results remain consistent with even a slight increase in point estimates from those in Tables 6 and 9.

threats to our identification strategy.

We estimated the impact of crime exposure on different academic outcomes: ordinal final exam grades, the probability of passing a final exam, the probability of obtaining an excellent grade, and the probability of taking the final exam. We measure exposure to crime as the number of crimes that occur within a distance of students' homes over a period of days previous to each final exam. Concretely, we have analysed spatial and time patterns by defining different distances (20, 40, 60, 80, 100 and 300 metres) and periods of days (7,15 and 30 days). Moreover, we divided all crimes into violent and non-violent crimes to analyse the potential impacts separately.

Our findings provide evidence that violent crime near students' residences has a negative impact on their final exam performance, while non-violent crimes do not have the same effect. We found that the negative impact diminishes with increased distance from students' residences and a longer time before final exams. The gender analysis suggest differential impacts of student performance for female and male students. Additionally, our analysis showed that the probability of taking final exams is not affected by exposure to crime, indicating no selection bias in our results.

Our results suggest that gender-specific impacts on student performance depend on the grade distribution. Male students primarily drive the negative impact of violent crime on ordinal grades, who have an increased probability of failing the exam. These results are confirmed by using the pass dummy outcome. Conversely, female students drive the impact on achieving excellent grades. Further, we explored potential heterogeneity in the impacts of crime exposure based on student ability. Overall, high-ability students are more affected by crime around their residences than low-ability students. High- and low-ability male students show a lower probability of a higher ordinal grade, while high-ability female students present a lower probability of passing final exams and, especially, a lower probability of obtaining an excellent grade. These findings align with previous literature showing that high-ability female students are more sensitive to external factors (see, for example, Beilock, 2011; De Paola and Gioia, 2016; Iriberri and Rey-Biel, 2019; Montolio and Taberner, 2021)

Our findings indicate clear gender-specific impacts on student performance depending on the type of violent crime. Female students are more affected by sexual and gender-based violence and threats at close distances. This is aligned with the literature on gender differences in fear of crime and perceived risk of victimization and the shadow of sexual assault thesis (Ferraro, 1996). In contrast, male students' performance is more influenced by injuries and robberies, which reflects a greater sensitivity to direct physical aggression. These findings are consistent with broader research on gendered differences in crime victimization and coping mechanisms (see, for example, Cops and Pleysier, 2011; Henson and Reyns, 2015).

We provide a better understanding of gender differences in university performance and the impact of local violent crime. Our study improves upon previous research by using the place of students' residence rather than school locations. Unlike Ang (2020), who analysed the impact of police violence on students near their homes, or Facchetti (2021), who relied on zip codes, our precise home-location data allow for a more granular analysis of crime exposure. While most research has centred on extreme incidents of violent crime — homicides, gunfights, or drug conflicts — our study focuses on more prevalent crime types in developed contexts, as in Facchetti (2021). Additionally, we have used a panel data framework while related literature relies on a repeated cross-section approach, strengthening our empirical strategy and findings. We have deepened the impact of crime exposure by analysing spatial and time patterns. Therefore, we contribute to a deeper understanding of the effect of local crime on student performance.

From a policy perspective, our findings shed light on the importance of promoting safety measures around student residences. Policymakers should consider targeted interventions to reduce violent crime in these areas, particularly during critical academic periods such as final exams. Additionally, support services for students who live in high-crime areas could help mitigate the negative impacts on academic performance. Ensuring a safe learning environment is crucial for academic success and to foster their future labour market outcomes. Moreover, all these measures might help to reduce gender inequalities, both in education and labour fields.

References

Aizer, A. (2013). Neighborhood Violence and Urban Youth. In Gruber, J., editor, *The Problems of Disadvantaged Youth*, pages 275–308. University of Chicago Press.

Ang, D. (2020). The Effects of Police Violence on Inner-City Students. *The Quarterly Journal of Economics*, 136(1):115–168.

Austin, W., Heutel, G., and Kreisman, D. (2019). School bus emissions, student health and academic performance. *Economics of Education Review*, 70:109–126.

Baetschmann, G. (2012). Identification and estimation of thresholds in the fixed effects ordered logit model. *Economics Letters*, 115(3):416–418.

Baetschmann, G., Ballantyne, A., Staub, K. E., and Winkelmann, R. (2020). feologit: A new command for fitting fixed-effects ordered logit models. *Stata Journal*, 20(2):253–275.

Baetschmann, G., Staub, K. E., and Winkelmann, R. (2015). Consistent estimation of the fixed effects ordered logit model. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 178(3):685–703.

Bastian, J. and Michelmore, K. (2018). The long-term impact of the earned income tax credit on children's education and employment outcomes. *Journal of Labor Economics*, 36(4):1127–1163.

Beilock, S. (2011). *Choke: What the Secrets of the Brain Reveal About Getting It Right When You Have To*. Simon and Schuster.

Beland, L. P. and Kim, D. (2016). The Effect of High School Shootings on Schools and Student Performance. *Educational Evaluation and Policy Analysis*, 38(1):113–126.

Bencsik, P. (2020). Stress on the sidewalk: The mental health costs of close proximity crime.

Bharadwaj, P., Bhuller, M., Løken, K. V., and Wentzel, M. (2021). Surviving a mass shooting. *Journal of Public Economics*, 201:104469.

Brück, T., Di Maio, M., and Miaari, S. H. (2019). Learning the Hard Way: The Effect of Violent Conflict on Student Academic Achievement. *Journal of the European Economic Association*, 17(5):1502–1537.

Buka, S. L., Stichick, T. L., Birdthistle, I., and Earls, F. J. (2001). Youth exposure to violence: Prevalence, risks, and consequences. *American Journal of Orthopsychiatry*, 71(3):298–310.

Cabral, M., Kim, B., Rossin-Slater, M., Schnell, M., and Schwandt, H. (2020). Trauma at School: The Impacts of Shootings on Students' Human Capital and Economic Outcomes. *NBER Working Paper No. 28311*.

Chang, E. and Padilla-Romo, M. (2022). When Crime Comes to the Neighborhood: Short-Term Shocks to Student Cognition and Secondary Consequences. *Journal of Labor Economics*.

Chiu, W. and Madden, P. (1998). Burglary and income inequality. *Journal of Public Economics*, 69(1):123–141.

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

Cops, D. and Pleysier, S. (2011). 'Doing gender' in fear of crime: The impact of gender identity on reported levels of fear of crime in adolescents and young adults. *British Journal of Criminology*, 51(1):58–74.

Cornaglia, F., Feldman, N. E., and Leigh, A. (2014). Crime and Mental Well-Being. *Journal of Human Resources*, 49(1):110–140.

Currie, J., Mueller-Smith, M., and Rossin-Slater, M. (2018). Violence while in Utero: The Impact of Assaults During Pregnancy on Birth Outcomes. *IZA DP No. 11655*.

Dahl, G. B. and Lochner, L. (2012). The Impact of Family Income on Child Achievement: Evidence from the Earned Income Tax Credit. *American Economic Review*, 102(5):1927–1956.

De Paola, M. and Gioia, F. (2016). Who performs better under time pressure? Results from a field experiment. *Journal of Economic Psychology*, 53:37–53.

Deb, P. and Gangaram, A. (2023). Effects of School Shootings on Risky Behavior, Health and Human Capital. *NBER WORKING PAPER SERIES No. 28634*.

Dustmann, C. and Fasani, F. (2016). The Effect of Local Area Crime on Mental Health. *The Economic Journal*, 126(593):978–1017.

Ebenstein, A., Lavy, V., and Roth, S. (2016). The long-run economic consequences of high-stakes examinations: Evidence from transitory variation in pollution. *American Economic Journal: Applied Economics*, 8(4):36–65.

Eurostat (2024). Estimated average age of young people leaving the parental household by sex.

Facchetti, E. (2021). Exposure to crime and pupils' outcomes: evidence from London.

Fajnzylber, P., Lederman, D., and Loayza, N. (2002). What causes violent crime? *European Economic Review*, 46(7):1323–1357.

Ferraro, K. F. (1996). Women's Fear of Victimization: Shadow of Sexual Assault? *Social Forces*, 75(2):667–690.

Graff Zivin, J., Song, Y., Tang, Q., and Zhang, P. (2020). Temperature and high-stakes cognitive performance: Evidence from the national college entrance examination in China. *Journal of Environmental Economics and Management*, 104:102365.

Harris, D. N. and Larsen, M. F. (2022). Taken by Storm: The Effects of Hurricane Katrina on Medium-Term Student Outcomes in New Orleans. *Journal of Human Resources*, pages 0819–10367R2.

Haugan, G. L. (2016). The effect of urban violence on student achievement in Medellin, Colombia. *Documentos CEDE No. 9*.

Heissel, J. A., Persico, C., and Simon, D. (2020). Does Pollution Drive Achievement? The Effect of Traffic Pollution on Academic Performance. *Journal of Human Resources*, (12745):1218–9903R2.

Henson, B. and Reyns, B. W. (2015). The only thing we have to fear is fear itself... and crime: The current state of the fear of crime literature and where it should go next. *Sociology Compass*, 9(2):91–103.

Iriberri, N. and Rey-Biel, P. (2019). Competitive Pressure Widens the Gender Gap in Performance: Evidence from a Two-stage Competition in Mathematics. *The Economic Journal*, 129(620):1863–1893.

Jackson, J. (2009). A psychological perspective on vulnerability in the fear of crime. *Psychology, Crime and Law*, 15(4):365–390.

Johansson, S. and Haandrikman, K. (2023). Gendered fear of crime in the urban context: A comparative multilevel study of women's and men's fear of crime. *Journal of Urban Affairs*, 45(7):1238–1264.

Koppensteiner, M. F. and Menezes, L. (2019). Violence and Human Capital Investments. *IZA Discussion Paper No. 12240*.

Krivo, L. J. and Peterson, R. D. (1996). Extremely Disadvantaged Neighborhoods and Urban Crime. *Social Forces*, 75(2):619–648.

Monteiro, J. and Rocha, R. (2017). Drug Battles and School Achievement: Evidence from Rio de Janeiro's Favelas. *The Review of Economics and Statistics*, 99(2):213–228.

Montolio, D. and Taberner, P. A. (2021). Gender differences under test pressure and their impact on academic performance: A quasi-experimental design. *Journal of Economic Behavior Organization*, 191:1065–1090.

Morrall, P., Marshall, P., Pattison, S., and Macdonald, G. (2010). Crime and health: A preliminary study into the effects of crime on the mental health of UK university students. *Journal of Psychiatric and Mental Health Nursing*, 17(9):821–828.

Neanidis, K. C. and Papadopoulou, V. (2013). Crime, fertility, and economic growth: Theory and evidence. *Journal of Economic Behavior Organization*, 91:101–121.

OCDE (2023). *PISA 2022 Results (Volume I)*, volume 46 of *PISA*. OECD Publishing, Paris.

Park, R. J. (2022). Hot Temperature and High-Stakes Performance. *Journal of Human Resources*, 57(2):400–434.

Sharkey, P. (2018). The Long Reach of Violence: A Broader Perspective on Data, Theory, and Evidence on the Prevalence and Consequences of Exposure to Violence. *Annual Review of Criminology*, 1(1):85–102.

Sharkey, P. and Sampson, R. (2017). Neighborhood Violence and Cognitive Functioning. In Schutt, R., Keshavan, M. S., and Seidman, L. J., editors, *Social Neuroscience*. Harvard University Press.

Sharkey, P., Schwartz, A. E., Ellen, I. G., and Lacoe, J. (2014). High stakes in the classroom, high stakes on the street: The effects of community violence on students' standardized test performance. *Sociological Science*, 1(May):199–220.

Valera, S. and Guàrdia, J. (2014). Perceived insecurity and fear of crime in a city with low-crime rates. *Journal of Environmental Psychology*, 38:195–205.

Wilson, W. W., Chua, R. F., Wei, P., Besser, S. A., Tung, E. L., Kolak, M., and Tabit, C. E. (2022). Association Between Acute Exposure to Crime and Individual Systolic Blood Pressure. *American Journal of Preventive Medicine*, 62(1):87–94.

Appendices

A Appendix

Table A.1: Impact of violent crime on the probability of a higher ordinal grade using linear estimator

	(1)	(2)	(3)	(4)	(5)	(6)
	Student and year-week FE			Student, exam and district-month FE		
	7 days	15 days	30 days	7 days	15 days	30 days
20 m.	-0.323**	-0.266***	-0.129**	-0.277*	-0.252***	-0.114*
	(0.142)	(0.089)	(0.062)	(0.148)	(0.089)	(0.061)
40 m.	0.021	-0.039	-0.040	0.026	-0.029	-0.020
	(0.062)	(0.044)	(0.032)	(0.061)	(0.043)	(0.031)
60 m.	-0.033	-0.069**	-0.035*	-0.011	-0.052*	-0.029
	(0.041)	(0.029)	(0.021)	(0.039)	(0.028)	(0.022)
80 m.	-0.014	-0.022	-0.013	-0.009	-0.006	-0.011
	(0.031)	(0.022)	(0.016)	(0.030)	(0.021)	(0.016)
100 m.	-0.024	-0.024	-0.014	-0.012	-0.009	-0.009
	(0.027)	(0.019)	(0.013)	(0.026)	(0.017)	(0.013)
300 m.	-0.006	-0.003	-0.003	-0.006	-0.003	-0.006
	(0.008)	(0.006)	(0.004)	(0.008)	(0.006)	(0.004)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam FE	No	No	No	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	No	No	No
District-month FE	No	No	No	Yes	Yes	Yes

Observations: 18.813 student-exams pairs (723 unique students) and 8 singleton observations dropped for each estimate in columns (1)-(3). 18.678 student-exams pairs (721 unique students) and 143 singleton observations dropped for each estimate in columns (4)-(6). Notes: each of these estimates comes from a separate estimation of equations (1) columns (1)-(3) and (2) columns(4)-(6), respectively (see Section 4 for more details). The ordinal dependent variable – grades – might take four possible values: fail, pass, merit and excellent. The independent variable of interest – number of crimes – has been computed as the number of crimes that occurred within $X \in \{20, 40, 60, 80, 100, 300\}$ meters from their residence over the previous $D \in \{7, 15, 30\}$ days of each final exam taken by the students. Standard errors clustered at the census tract level are in parentheses, and *** denotes significance at the 1% level, ** the 5% level and * the 10% level.

Table A.2: Robustness check of the categorisation of crime typologies: robbery as non-violent crime. Impact on the probability of a higher ordinal grade

	(1)	(2)	(3)	(4)	(5)	(6)
	Violent crime (with no robbery crimes)			Non-violent crime (with robbery crimes)		
	7 days	15 days	30 days	7 days	15 days	30 days
20 m.	-0.2163	-0.4025***	-0.1546	-0.0643	-0.0038	-0.0000
	(0.2119)	(0.1453)	(0.0977)	(0.0715)	(0.0488)	(0.0340)
40 m.	0.0814	-0.0316	-0.0295	0.0006	0.0054	0.0038
	(0.0936)	(0.0720)	(0.0513)	(0.0330)	(0.0210)	(0.0163)
60 m.	-0.0539	-0.0948*	-0.0204	-0.0114	-0.0091	-0.0069
	(0.0651)	(0.0499)	(0.0351)	(0.0209)	(0.0132)	(0.0091)
80 m.	-0.0217	-0.0435	-0.0006	0.0056	-0.0052	-0.0082
	(0.0489)	(0.0379)	(0.0260)	(0.0167)	(0.0100)	(0.0064)
100 m.	-0.0165	-0.0274	-0.0014	0.0034	0.0002	-0.0025
	(0.0417)	(0.0310)	(0.0214)	(0.0092)	(0.0050)	(0.0032)
300 m.	-0.0134	-0.0088	-0.0026	0.0037	0.0026	0.0008
	(0.0142)	(0.0098)	(0.0072)	(0.0031)	(0.0017)	(0.0010)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes

See observations and notes in Table 6.

Table A.3: Robustness check of the categorisation of crime typologies: family-related offences as non-violent crime. Impact on the probability of a higher ordinal grade

	(1)	(2)	(3)	(4)	(5)	(6)
	Violent crime (with no family crimes)			Non-violent crime (with family crimes)		
	7 days	15 days	30 days	7 days	15 days	30 days
20 m.	-0.3680**	-0.3281***	-0.1603**	-0.0065	0.0362	0.0154
	(0.1574)	(0.0945)	(0.0665)	(0.0743)	(0.0545)	(0.0363)
40 m.	0.0218	-0.0512	-0.0326	0.0114	0.0169	0.0089
	(0.0678)	(0.0473)	(0.0335)	(0.0351)	(0.0235)	(0.0173)
60 m.	-0.0454	-0.0823***	-0.0383*	-0.0048	-0.0009	-0.0017
	(0.0439)	(0.0314)	(0.0217)	(0.0224)	(0.0150)	(0.0101)
80 m.	-0.0172	-0.0297	-0.0132	0.0101	-0.0028	-0.0068
	(0.0341)	(0.0243)	(0.0164)	(0.0174)	(0.0110)	(0.0067)
100 m.	-0.0177	-0.0305	-0.0165	0.0058	0.0019	-0.0020
	(0.0289)	(0.0202)	(0.0136)	(0.0089)	(0.0049)	(0.0029)
300 m.	-0.0023	-0.0014	-0.0013	0.0037	0.0027	0.0009
	(0.0090)	(0.0067)	(0.0046)	(0.0032)	(0.0018)	(0.0010)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes

See observations and notes in Table 6.

Table A.4: Impact of violent crimes on the probability of sitting a final exam by gender

	Female			Male		
	7 days	15 days	30 days	7 days	15 days	30 days
20 m.	-0.054	-0.047**	-0.009	-0.018	0.006	0.029
	(0.034)	(0.020)	(0.014)	(0.038)	(0.024)	(0.023)
40 m.	0.006	0.006	0.005	-0.005	0.007	0.009
	(0.014)	(0.010)	(0.006)	(0.016)	(0.011)	(0.008)
60 m.	-0.004	0.002	0.000	-0.015	0.001	0.006
	(0.009)	(0.006)	(0.005)	(0.012)	(0.008)	(0.006)
80 m.	0.002	-0.001	-0.002	-0.007	0.006	0.008*
	(0.007)	(0.005)	(0.004)	(0.009)	(0.006)	(0.004)
100 m.	0.004	-0.001	-0.001	0.010	0.010*	0.008**
	(0.006)	(0.004)	(0.003)	(0.007)	(0.005)	(0.004)
300 m.	-0.001	-0.001	-0.001	-0.000	0.001	0.001
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam FE	Yes	Yes	Yes	Yes	Yes	Yes
District-month FE	Yes	Yes	Yes	Yes	Yes	Yes

See observations and notes in Table 8.

Table A.5: Impact of violent crimes on the probability of passing or obtaining an excellent, excluding grade categories

	Pass Dummy (excluding merit and excellent)			Excellent Dummy (excluding fail and pass)		
	7 days	15 days	30 days	7 days	15 days	30 days
20 m.	-0.077*	-0.031	-0.029	0.014	-0.014	-0.011
	(0.046)	(0.030)	(0.020)	(0.076)	(0.054)	(0.029)
40 m.	-0.010	-0.010	-0.018**	-0.026	-0.039*	-0.009
	(0.018)	(0.013)	(0.009)	(0.031)	(0.022)	(0.015)
60 m.	-0.004	-0.012	-0.010	-0.042**	-0.042***	-0.017*
	(0.013)	(0.008)	(0.006)	(0.020)	(0.014)	(0.010)
80 m.	-0.007	-0.004	-0.008	-0.018	-0.024**	-0.005
	(0.010)	(0.007)	(0.005)	(0.014)	(0.010)	(0.008)
100 m.	-0.011	-0.004	-0.004	-0.001	-0.013*	-0.004
	(0.009)	(0.005)	(0.004)	(0.011)	(0.008)	(0.006)
300 m.	-0.004	-0.002	-0.002	0.003	-0.002	0.000
	(0.003)	(0.002)	(0.001)	(0.004)	(0.003)	(0.002)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam FE	Yes	Yes	Yes	Yes	Yes	Yes
District-month FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: this table reproduces estimates from Table 9 with the exception that some grade categories have been excluded from the analysis. See observations in Table 9.

Table A.6: Placebo test of measurement error of address: random address within MAB and over 15 days

	(1)	(2)	(3)	(4)	(5)	(6)
	Ordinal Grade		Pass Dummy		Excellent Dummy	
	Violent	Non-violent	Violent	Non-violent	Violent	Non-violent
20 m.	-0.193	-0.122	0.009	0.003	0.009	-0.006
	(0.131)	(0.079)	(0.045)	(0.017)	(0.024)	(0.009)
40 m.	0.184	-0.067	0.032	-0.002	0.028*	-0.007
	(0.130)	(0.048)	(0.024)	(0.012)	(0.015)	(0.006)
60 m.	0.046	-0.036	0.007	0.006	0.009	-0.006
	(0.087)	(0.032)	(0.018)	(0.009)	(0.008)	(0.004)
80 m.	-0.005	-0.030	-0.005	0.004	0.004	-0.004
	(0.059)	(0.028)	(0.012)	(0.006)	(0.006)	(0.003)
100 m.	0.000	-0.003	-0.007	0.002	0.007	0.001
	(0.043)	(0.022)	(0.011)	(0.005)	(0.005)	(0.003)
300 m.	-0.002	0.001	-0.000	0.001	-0.001	-0.000
	(0.013)	(0.006)	(0.003)	(0.001)	(0.002)	(0.001)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam FE	No	No	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	No	No	Yes	Yes
District-month FE	No	No	Yes	Yes	Yes	Yes

See observations and notes in Table 6.

Table A.7: Robustness check of measurement error of address: subsample of students born in MAB and over the 15 days

	(1)	(2)	(3)	(4)	(5)	(6)
	Ordinal Grade		Pass Dummy		Excellent Dummy	
	Violent	Non-violent	Violent	Non-violent	Violent	Non-violent
20 m.	-0.327***	0.040	-0.047**	0.017	-0.025**	0.004
	(0.096)	(0.065)	(0.024)	(0.012)	(0.011)	(0.007)
40 m.	-0.075	0.011	-0.011	0.011**	-0.013***	0.001
	(0.049)	(0.023)	(0.011)	(0.005)	(0.005)	(0.003)
60 m.	-0.086***	-0.004	-0.011	0.002	-0.012***	-0.000
	(0.033)	(0.015)	(0.007)	(0.003)	(0.003)	(0.002)
80 m.	-0.024	-0.010	-0.002	-0.000	-0.008***	-0.001
	(0.025)	(0.011)	(0.006)	(0.002)	(0.003)	(0.001)
100 m.	-0.021	-0.000	-0.002	0.002**	-0.004**	-0.000
	(0.021)	(0.005)	(0.005)	(0.001)	(0.002)	(0.001)
300 m.	0.003	0.003	0.001	0.001	0.001	-0.000
	(0.007)	(0.002)	(0.002)	(0.000)	(0.001)	(0.000)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam FE	No	No	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	No	No	No	No
District-month FE	No	No	Yes	Yes	Yes	Yes

Observations: 16,230 student-exams pairs (612 unique students) for the ordinal grade estimates and 16.123 student-exams pairs (618 unique students) for the pass and excellent dummies estimates. Notes: see notes in Table 6 for ordinal grade estimates and in Table 9 for the pass and excellent dummies estimates.

Table A.8: Placebo test of exam date: one year after and over 15 days

	(1)	(2)	(3)	(4)	(5)	(6)
	Ordinal Grade		Pass Dummy		Excellent Dummy	
	Violent	Non-violent	Violent	Non-violent	Violent	Non-violent
20 m.	-0.106	0.051	0.005	-0.000	-0.007	0.003
	(0.090)	(0.048)	(0.023)	(0.010)	(0.009)	(0.004)
40 m.	0.013	0.012	0.006	-0.007	-0.000	-0.002
	(0.044)	(0.022)	(0.011)	(0.005)	(0.005)	(0.002)
60 m.	0.006	0.021	0.006	-0.003	-0.004	0.001
	(0.027)	(0.016)	(0.007)	(0.003)	(0.003)	(0.002)
80 m.	0.023	0.008	0.007	-0.002	-0.000	-0.000
	(0.022)	(0.011)	(0.005)	(0.002)	(0.002)	(0.001)
100 m.	-0.006	0.009*	0.005	0.003	-0.001	0.000
	(0.018)	(0.005)	(0.004)	(0.002)	(0.002)	(0.001)
300 m.	-0.003	0.003*	-0.001	0.001**	-0.001	-0.000
	(0.006)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam FE	No	No	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	No	No	Yes	Yes
District-month FE	No	No	Yes	Yes	Yes	Yes

See observations and notes in Table 6 for ordinal grade estimates and in Table 9 for the pass and excellent dummies estimates.

Table A.9: Placebo test of exam date: random date over 15 days

	(1)	(2)	(3)	(4)	(5)	(6)
	Ordinal Grade		Pass Dummy		Excellent Dummy	
	Violent	Non-violent	Violent	Non-violent	Violent	Non-violent
20 m.	0.008	-0.005	-0.042*	0.004	0.009	0.002
	(0.112)	(0.046)	(0.025)	(0.011)	(0.014)	(0.005)
40 m.	-0.010	0.009	-0.007	0.006	-0.002	0.002
	(0.042)	(0.020)	(0.011)	(0.005)	(0.005)	(0.002)
60 m.	-0.046	0.009	-0.008	0.004	-0.004	0.002
	(0.029)	(0.013)	(0.007)	(0.003)	(0.004)	(0.001)
80 m.	-0.041*	0.004	-0.007	0.002	-0.003	0.001
	(0.022)	(0.009)	(0.005)	(0.002)	(0.002)	(0.001)
100 m.	-0.027	0.002	-0.002	0.001	-0.002	-0.000
	(0.017)	(0.004)	(0.004)	(0.001)	(0.002)	(0.001)
300 m.	-0.009	0.001	-0.002	-0.000	0.000	-0.000
	(0.006)	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam FE	No	No	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	No	No	Yes	Yes
District-month FE	No	No	Yes	Yes	Yes	Yes

Observations: 18,755 student-exams pairs (712 unique students) for the ordinal grade estimates and 17.821 student-exams pairs (718 unique students) for the pass and excellent dummies estimates. Notes: see notes in Table 6 for ordinal grade estimates and in Table 9 for the pass and excellent dummies estimates.

IEB Institut d'Economia de Barcelona