Provision Effects of Local Public Goods on Crime and Education: Evidence from Colombia

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Thesis
Master in Economics

Universidad del Rosario
Facultad de Economía
2020

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February 17, 2020

Abstract

The provision effects of local public goods on crime and education are not clear in the literature. While some argue that provision does not affect these outcomes, other find that effects depend on the benefits it offers to the community. This paper studies the effect of the construction of cultural centers in Medellín, Colombia on crime and test scores in mathematics and language. This policy is interesting since the communities participated in the design of these cultural centers. Using a dynamic difference-in-differences strategy, I find that schools near centers improve their test performance, especially for younger children. Regarding crime, I find that in neighborhoods near centers, there is a reduction in motorcycle and car theft crimes.

Keywords: Education, Crime, Public Goods, Public Policy

JEL classification: H41, I28, K42, J48

*I am deeply grateful to Santiago Saavedra and Paul Rodríguez for their generosity in allowing me to learn from them and for their encouragement. I thank participants at Universidad del Rosario Applied Micro Workshop and Brown Bag Seminar for their interesting and useful comments to previous versions of this research. I also thank EPM and Area Metropolitana del Valle de Aburrá for information and data shared. I especially thank my family and friends for their unconditional support. All errors are on my own.

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1 Introduction

The question about how the provision of local public goods affects welfare outcomes is relevant. Especially, for education and crime outcomes there is no agreement in the literature about the direction of the effects. On the one hand, the literature on public goods and education does not find solid results on the effect of this provision on test scores (Borkum et al. (2012), Casely-Hayford & Hartwell (2010), De Witte & Geys (2011) and Rodríguez-Lesmes et al. (2014)). On the other hand, literature about crime outcomes finds positive effects when communities use these assets but have no effects or even negative effects when they are not received by the community (Brantingham & Brantingham (1995), Chalfin et al. (2019), Domínguez & Asahi (2017) Farrington & Welsh (2002), and Groff & McCord (2012)).

This paper takes advantage of the implementation of cultural center construction policy in abandoned places of disadvantaged communities which also offer sports and cultural services. I analyze the effect of cultural centers built in Medellin, Colombia on education and crime outcomes. I compare schools and neighborhoods that are close to the centers, with those that are further, after the opening of the cultural centers. For education outcomes, I use administrative data of test scores in 3^{rd}, 5^{th}, 9^{th}, and 11^{th} grade. I also use a survey that allows me to identify characteristics specific to the school. Concerning crime outcomes, I use administrative records for homicides, different thefts and domestic violence, provided by The National Police. Since those centers were not opening at the same time, I use a dynamic difference in differences method.

There is evidence showing that parks provide relief to daily routines through social interaction, maintaining family ties, influence tolerance and raise the mind of people and improve the health and well-being of urban life (Cattell et al. (2008), Larson et al. (2016) and Wu et al. (2019)). The literature also shows that there is an improvement in the health of people living in communities with parks, due to the improvement in physical well-being and proximity to green places (Kabisch et al. (2015) and Maas et al.

(2006)).

It is also interesting that parks improve the safety of the beneficiary communities due to the investment in lighting and security (Atkins et al. (1991), Chalfin et al. (2019), Doleac & Sanders (2015), Domínguez & Asahi (2017) and Farrington & Welsh (2002)). Some studies have also found that investments in state presence also have effects of reduction on crime, which can be directly related to the provision of public parks (Blattman et al. (2017), Di Tella & Schargrodsky (2004), Ferraz et al. (2016) and Mihinjac & Saville (2019)).

Nevertheless, when communities do not use parks or buildings, they become abandoned spaces or ”white elephants”. In consequence, insecurity and crime can increase since these places become conducive to these acts (Brantingham & Brantingham (1995), Groff & McCord (2012) and Kluwer-Nijhoff et al. (1995)) .

Investment in parks can also trigger investment in cultural and sports fields, and this, in turn, can affect the outcomes of communities especially of younger people. On the one hand, there is mixed evidence that finds positive or null effects about the effect of investment and participation in sports activities on academic performance, since this depends on socio-economic factors such as race or family structure and it is directly related to the offer of open spaces (Eitle & Eitle (2002), Jordan (1999), Mixon Jr (1995) and Pope & Pope (2009)). Concerning cultural activities or use of leisure, literature shows that students who develop complementary activities to the school obtain better results in test scores, and it is more likely that they are carried out in public spaces, especially in disadvantaged communities. (Casely-Hayford & Hartwell (2010), DeStefano et al. (2007) and Marrocu & Paci (2012)).

In particular, although the literature has studied about different investment policies in parks that directly affect educational results, there was an urban renewal in them, but there was no process of citizen participation (Borkum et al. (2012), De Witte & Geys (2011) and Rodríguez-Lesmes et al. (2014)). In addition, there is also no evidence of studies that relate the provision of cultural centers with educational and crime outcomes. Since, although cultural centers are parks, they also provide more services that may be influencing the well-being of communities. My paper studies directly the relationship between this type of cultural centers and welfare in terms of education and crime outcomes.

Regarding education, I find that schools near centers improve their test performance, especially for children in primary school. While there is no clear effect on older students. The results also show that these effects are not driven by a change in the composition of the classes after the construction of the centers. Regarding crime, I find that in neighborhoods near centers, there is a reduction in motorcycle and car theft crimes.

Results are robust to change the treatment group using different distance buffers around centers and to the specification of continuous treatment using the distance from the analysis unit to the nearest center. The results are also robust to a specification by the intensity that uses the number of centers to which a school or neighborhood is close.

This paper contributes to the growing literature on the provision of local public goods and welfare, with two distinct innovations. Firstly, the provision of cultural centers with community participation. Secondly, sports and culture promotion policies generate well-being in terms of education and crime. Particularly, the literature I mentioned generally finds null effects of the implementation of local public goods on crime and education, while this paper shows positive effects on both outcomes. This may indicate that the effectiveness of this policy is being guided by citizen participation in the design of cultural centers.

The rest of the paper is organized as follows. In the next section, I describe the cultural center's program. Section 3 illustrates the data and empirical strategy. Section 4 presents the econometric model. In Section 5, I study the impact of the cultural center's program on education and crime outcomes, with robustness exercises. Section 6 discusses the implications of the results and Section 7 concludes.

2 Context

Articulated Life Units (UVAs for its Spanish acronym) is a project established in Medellin. This project has the objective to transform urban centers and promote citizen participation, culture, recreation, and sports. In this sense, the public services provider Empresas Públicas de Medellin (EPM for its Spanish acronym) decided to use old water tanks to build cultural centers. These tanks were abandoned places in the city called ”darkness islands”. In many cases, these were used to execute criminal activities.

The Metropolitan area of Medellin has 144 water tanks. In the beginning, they were built in the suburbs of the city, but by the expansion, those tanks were immersed in the urban area. Neighborhoods with tanks are poor and devoid of public spaces. For this project, EPM selected 20 neighborhoods taking account of useful areas, population density, needs of neighboring communities, geological restrictions, expansion of the aqueduct service and its surroundings. To promote equity in the territory, they also took into account as a criterion those neighborhoods that did not adequate spaces for sports and cultural events.

This policy is especially interesting because communities participate in the design of each center. Therefore, each center responds to the results of design workshops held with the community. In particular, EPM developed meetings with interest groups such as neighborhood leaders, children, and household head mothers to ask them about the necessities of the community.

These centers provide free services for many age groups for instance libraries, computer rooms, playgrounds, theaters, toy libraries, and sports, music, and computer classes. Those services were proposed to take advantage of free time in useful activities and to supply culture services that communities need. This policy was also implemented complementary to the urban lighting master plan for Medellín. Thus, those centers have a large investment in lighting and private security.

The centers started in Medellin, But two more centers were implemented in Itagui and

Bello (municipalities that limit with Medellin south and north, respectively). Nevertheless, those 2 centers were not built-in tanks but in donated parts of the EPM water treatment plants.

The project was financed by EPM, Instituto para la Recreación y el Deporte (INDER for its Spanish acronym) and Medellin city hall. These entities invested around 60 million dollars for the construction and implementation of the centers and about 2.5 million citizens of Medellín are benefited. Particularly, this project was very successful in terms of communities satisfaction. Even, some of the centers received international awards for its innovation, transferability, ethical standards and social equity.

The construction of the centers began in 2013 and the first two centers were completed in 2014. Then, the centers were delivered gradually between 2015 and 2017. Currently, 18 centers are operating and 2 more are still in construction. Figure A.1 shows images of the tanks before and after the implementation of this policy of cultural centers.

Medellin is a city with large policies to improve education and fight crime. On the one hand, programs have sought to improve education in terms of coverage, quality, and permanence. This has become visible in the field of public investment, where education is the most important item. Besides, efforts have also been made to monitor coverage rates, dropout, repetition, and school achievement.

On the other hand, in terms of crime, the local administration has aligned its efforts to reduce homicides and organized crime such as drug sales and extortion. But efforts have also been made in lighting, security cameras, and the number of police in the city to fight crimes such as thefts.

In this paper, I argue two ways by which communities could benefit from this policy, improving the benefits the centers provide by aesthetics and green spaces, in particular in terms of crime and education. First, children in those communities could improve their scholar results, because they could substitute leisure with activities offered by the center. Besides, those culture and sports classes were implemented in poor neighborhoods where the majority of households could not pay for those private services. In this sense, this policy satisfies the recreation needs of the communities.

Second, lighting and private security could affect criminal outcomes. As mentioned, those spaces in the city were abandoned and they could generate crime. Now, they are places where the communities meet and take advantage of the services offered. On the other hand, this could be related to education outcomes. While returns to education increase, crime becomes less striking and children can find a motivation to continue in schools. In the remainder of the analysis, I show the existence of those two effects in benefited communities.

3 Data and Empirical Strategy

To econometrically examine the connection between culture centers and educational and crime outcomes, I use administrative data on test scores and crime using a dynamic difference-in-differences approach. In order to identify the causal effect, I defined treatment and control groups based on the Euclidean distance of schools and neighborhoods to the closest UVA. The central assumption is that without the construction of UVAs, differences in the outcome variables would have been preserved between units relatively close and far from UVAs. As a result, the impact would be the difference in the outcomes after the implementation of UVAs, net of pre-existing differences. Figure 1 shows an example of the procedure that I implement to define treatment and control groups. Figure A.2 shows the procedure for all the centers. In the following subsections, I present the group's definition and describe the data used for both education and crime.

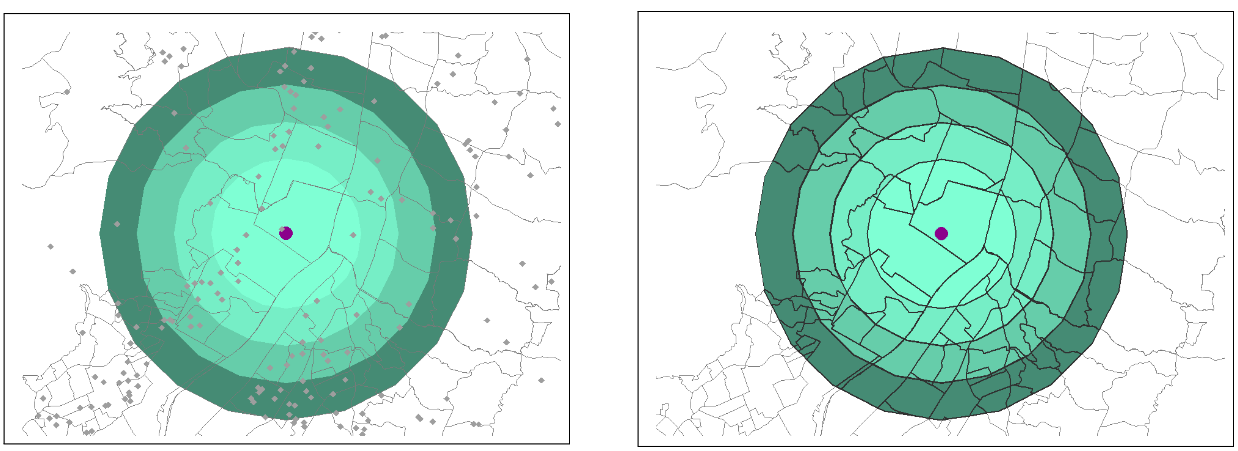
3.1 Treatment and control definition: proximity to UVAs

First, to find the treatment and control schools, I georeference the 18 culture centers. Then, I calculate the distance of each school to all UVAs. I define schools as treated if the distance is less or equal than 1.5 kilometers. As robustness, I check between 1 and 2.5 kilometers in my specifications. I also use the distance continues between units and centers and the number of UVAs that each school is close to.

Second, to find the treatment and control neighborhood groups, I use a similar procedure. I create the buffers of different sizes around the centers and then I intersect them with the neighborhoods. I do this instead of calculating the distance from the edge or center, but having a measure of the proportion of the neighborhood that is intersected by the buffers. Then, I again select as neighborhoods treated those that are intersected by the buffers in some proportion.

As I mention before only three municipalities have culture centers and for this reason, the majority of observations are found in Medellin, Bello, and Itagui. Nevertheless, as I show in Tables A.1 and A.2, six municipalities have units treated, so I use data from all ten municipalities in Medellin's Metropolitan Area and I also present results without those four distant municipalities that have no units treated.

Figure 1: Control and treatment groups procedure



(a) Schools (b) Neighborhoods

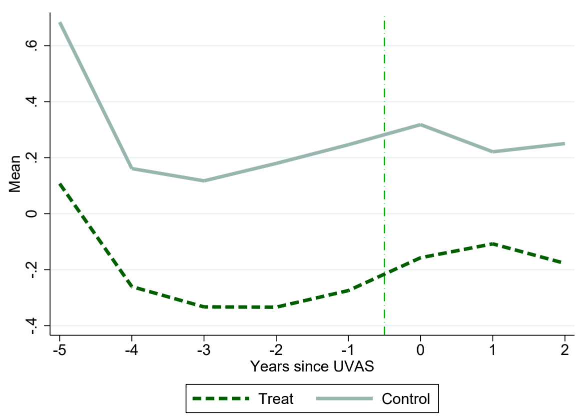
Notes: This figure shows on the left, the procedure for the school level. On the right, procedure for neighborhood level. Schools are gray diamonds. Purple point is a culture center. Circular buffers for 1, 1.5, 2 and 2.5 kilometers. Those schools or neighborhoods inside the buffers are treated depending on the specification.

3.2 Education

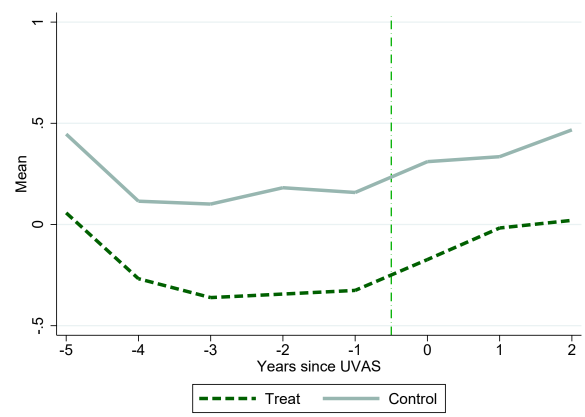
My analysis covers the period from 2012 to 2017, two years before the first UVA was delivered. For school outcomes, I use administrative records of test scores in the national exam Saber for 3^{rd}, 5^{th}, 9^{th}, and 11^{th} grade reported by year and at the school level from the Colombian Institute for Evaluation of Education (ICFES for its Spanish acronym).

Figure 2 shows raw data for the treatment and control group in math and language tests in standardized values for a window 5 years before and 2 years after the opening of the culture center, while Figure B.3 shows raw data by test desegregation. This graph shows that before treatment both groups experienced a similar trajectory in the results of these tests. This gives a first look at the assumption of parallel trends, which I test and explain in more detail in the Results section.

Figure 2: Raw data all tests



(a) Math



(b) Language

Source: ICFES
Notes: This figure shows raw data for standardized test scores for treated and untreated groups. Data covers the window 5 years before and 2 years after the center opening year. Panel A reports data on Math test scores. Panel B reports data on the Language test score. The solid line represents the control group and the dotted line represents the treated group. All tests include Saber 3, 5, 9 and 11.

Another interesting fact in this graph is that untreated schools have better results in both tests and this difference is more noticeable in math. This can be generated by the way of assigning the places where the cultural centers were built. These places should be in unfavorable conditions for recreation and culture, which may be related to unfavorable educational conditions as well.

I also use the C600 survey carried out by the Colombia's National Statistics Office (DANE for its Spanish acronym), at all schools annually and from where I can identify characteristics specific to the school. Table 1 reports the descriptive statistics for these variables in the pre-treatment period, in the last column I present the P-value of a mean difference test.

Columns 1 and 2 of Table 1 show that treated schools are different from untreated schools in the number of students enrolled at the primary level. They also differ in the number of teachers and the number of school employees. In particular, treated schools are bigger than untreated schools in those variables and this difference is statistically significant. For this reason, I include these variables measured in 2010 interacted by year dummies variables as controls in the main specification. Other variables as a number of students enrolled in preschool, secondary and high education by gender do not present significant differences between the two groups.

I also use C600 to find the effect of cultural centers on other outcomes such as the rate of approved, dropouts and transfers. It is important to clarify that these variables are not measured at the same level of education as ICFES. These rates are measured for each grade and generally for each educational level. Then, I use these rates for the primary, secondary and high school levels.

These rates are also disaggregated by gender. This allows me to make a distinction of the effect for women and men, which I cannot do for the main outcomes of the Saber tests, since these are reported at grade level only. This to test if girls are more influenced by cultural activities while boys by sports activities.

Panel A of Figures C.5 to C.7 shows raw data for rates of approved, dropouts and transfers for treated and untreated groups in percentages. These graphs also show that control schools have higher rates but they follow a similar trajectory during the study period. As usual in the literature, these figures show that women have better academic performance

Table 1: Descriptive statistics controls Pre-Treatment (2010)

Variable	(1) Treatment (sd)	(2) Control (sd)	(3) Difference [p-value]
Men preschool students	66.451	62.475	3.976
	(55.114)	(76.349)	[0.535]
Women preschool students	67.570	60.138	7.432
	(64.603)	(63.748)	[0.215]
N	193	282	
Men primary students	345.382	297.199	48.183*
	(266.730)	(319.589)	[0.078]
Women primary students	334.040	280.389	53.651**
	(254.939)	(266.763)	[0.025]
N	199	306	
Men secondary students	418.786	403.894	14.892
	(336.894)	(450.239)	[0.686]
Women secondary students	438.052	407.812	30.240
	(320.274)	(386.760)	[0.354]
N	210	293	
Men high school students	158.089	168.859	-10.770
	(132.927)	(227.263)	[0.557]
Women high school students	176.537	187.271	-10.734
	(139.326)	(206.533)	[0.532]
N	190	277	
Men teachers	13.663	11.458	2.205**
	(12.275)	(13.070)	[0.037]
Women teachers	28.434	24.455	3.979**
	(19.512)	(21.901)	[0.022]
Men staff	19.867	16.869	2.998**
	(16.450)	(18.774)	[0.042]
Women staff	36.863	33.866	2.997
	(24.885)	(29.788)	[0.193]
N	249	358	

Source: C600
Notes: This table shows descriptive statistics for variables in 2010 at the school level. Column (1) presents results for the treatment group and Column (2) presents results for the control group. While Column (3) presents the results for mean difference tests between both groups. Panel 1, 2,3, 4 show students for preschool, primary, secondary and high school level of education. Panel 5 presents teachers and staff for any education level.

than men in both treatment and control groups.

3.3 Crime

For crime outcomes, I use administrative records provided by the National Police in the period from 2012 to 2017. Those variables are reported by year and neighborhood. I use homicides, person, car, motorcycle and residence thefts, and domestic violence.

Figure 3 shows raw data for the treatment and control groups by crime in units by kilometer for a window 5 years before and 2 years after the opening of the culture center. This graph illustrates that the control group has higher criminality in almost all outcomes. Similar trajectories for both groups are observed in person, car and residence thefts before treatment. However, different dynamics can be observed for homicides, motorcycle theft and domestic violence in these groups. In the Results section, I present formal evidence to verify that the trends in all crimes are not different before treatment.

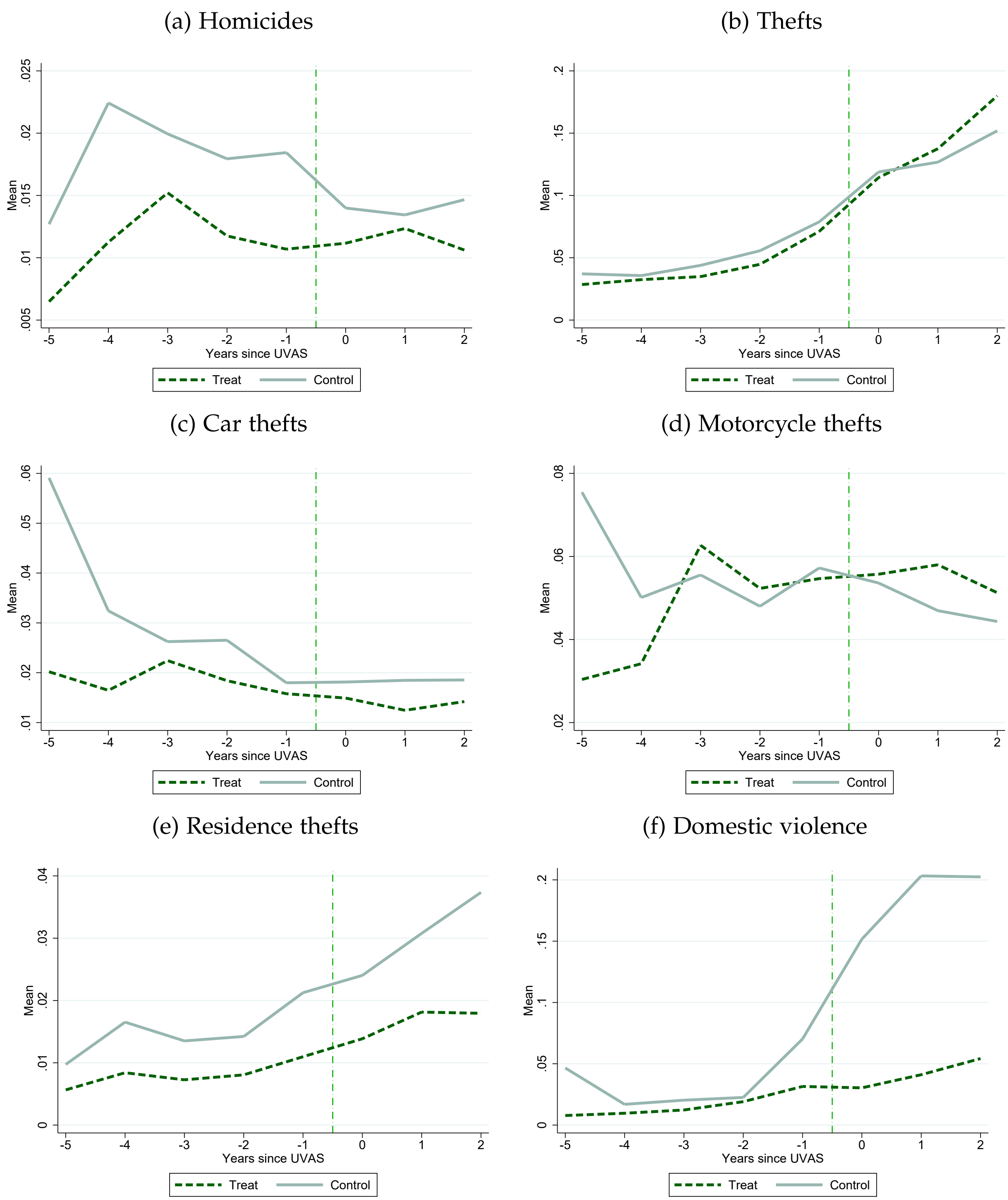
To summarize, the data shows that cultural centers were established in places with poor educational and safety performance. This somehow leads to a greater challenge for this policy to present improvements in the well-being of these communities, and more room to improve.

4 Econometric Model

In this section, I present in depth the econometric model and related identifying assumptions at both the school-level and the neighborhood-level.

Note that both the unit and time treated were not random select. Since authorities decided to construct centers in poor neighborhoods, they are less favored areas and they have worse performance in both education and crime outcomes. This means, probably these units are not comparable with zones not treated.

Figure 3: Raw data by crime



Source: National Police
Notes: This figure shows raw data for crime reports for treated and control groups in units by kilometer. Data covers the window 5 years before and 2 years after the center opening year. Panels A to F report data on homicides, person, car, motorcycle and residence thefts, and domestic violence. The solid line represents the control group and the dotted line represents the treated group.

In the same way, neighborhood administrations can be different in places where centers were constructed firstly and those differences can affect the effects that I want to identify. Nevertheless, in this section, I discuss some controls that I include in the specifications, and in the Results section, I show that are no significant differences within both treated and no treated groups for the variables that can be tested.

4.1 Education

To test the relationship between the centers and education outcomes and to analyze the statistical significance and magnitude of the estimates, I use the following parametric specification:

$$Educ_{cst} = \beta * PostUVA_t * Close_c + \sum_t X_c \alpha_t + \gamma_c + \gamma_s + \gamma_t + \varepsilon_{cst} \tag{1}$$

Where $Educ_{cst}$ is the educational outcome (it means results Saber on Math and Language, approved, dropouts, and transferred rates), in school c, at test s and at time t. $PostUVA_t$ is an indicator variable taking value 1 for all years after the center opening and $Close_c$ is an indicator variable taking value 1 for the schools close to centers, and 0 otherwise. $PostUVA_t$ and $Close_c$ are always 0 for never treated schools. I also include controls variables X_c at school level measure in 2010, that is, before the treatment. Then, I interact those variables with time dummies to find differential trends depending on the characteristics of schools. Thus, $\alpha_t = 1$ in year t and zero otherwise. γ_c, γ_s and γ_t are a school, test and year fixed effects, which absorb fixed differences across schools, across tests and years. Errors ε_{cst} are clustered to school level.

In Equation (1), therefore, the coefficient of interest is β and it measures the change in the outcome variables of the schools close to centers compared to schools far to the centers, after conditional on the set of schools, test and year fixed effects. This equation tries to remove the most important sources of bias that can be measured in estimating the impact of cultural centers on educational outcomes.

Inclusion of time fixed effects allows controlling for any time events affecting equally schools test scores. While the school fixed effects control for any characteristic of each school that may affect the test scores. Also, the inclusion of the control variables described in Table 1 allows control for pre-existing differences of variables that vary at school and time level, and that as shown in the table were statistically different for the treatment and control group. These control inclusions allow making sure that results are not just driven by differential trends based on school characteristics that could correlate with educational outcomes.

In the main specification, I use the results of all tests, that is, test scores 3, 5, 9 and 11 in standardized values. But I also present the results for each of the tests separately. This to find effects differentiated by the age and the school level of the children.

I define schools close to center if the distance between these is lower to 1.5 kilometers, this equals approximately 10 minutes walking, but in the Robustness Checks section, I present strength to this parameter. Note that I can identify schools near centers and not the places where the students live. Then, there are at least three ways in which students can be affected by the center. 1. The school uses the tools provided by the center to provide additional recreation and sports classes. 2. Students in schools near the centers use leisure in the activities offered. 3. Students who live near the centers, regardless of whether they study nearby or not, use leisure in the activities offered in the center.

Then, given the form of the data I use, I can identify groups 1 and 2 but not group 3. There may be students who benefit from the services offered by the center but who do not attend a school that is classified as nearby to the center. This can generate a bias in my estimate. However, I argue that households are usually located near children's schools, so I will not find many cases in group 3.

In addition to the above, there may be a class composition bias. It means, households after seeing the construction of the centers decide to change their children from schools to be benefited by the center. For this reason, I use other outcomes, which allow me to check the effect of cultural centers on the rates of approved, dropouts and transfers from schools near centers. I discuss these results in the next section.

I also estimate the dynamic version of the model:

$$Educ_{cst} = \gamma_c + \gamma_s + \gamma_t + \sum_{k=-5}^{k=-2} \beta_k * Close_c + \sum_{k=0}^{k=2} \beta_k * Close_c + \varepsilon_{cst} \tag{2}$$

Where c, s and t stand for school, test and year, respectively, and β_k capture the relative event time indicators. That is, β_k is an indicator variable taking value 1 if it is year k relative to the cultural center opening. $Close_c$ is an indicator variable taking value 1 for the schools close to centers, and 0 otherwise. These indicator variables are always 0 for schools that are never treated. I choose a window of 8 years around the event. As is typical in event study frameworks, I make the normalization $\mu{-1} = 0$, so that all coefficients represent differences in outcomes relative to the year before the center opening. The specification includes schools fixed effects (γ_c), test fixed effects (γ_s) and year fixed effects (γ_t). ε_{cst} are standard errors clustered at the level of the schools.

Equation (2), allows me to see the evolution of the effect of cultural centers on educational outcomes, conditional on the set of school, test and year fixed effects. At the same time, this specification will also allow me to see how the educational dynamics of the treated schools were compared to those not treated before the implementation of the centers. That is, it will allow testing that assumption of parallel trends is fulfilled, which supports the non-existence of differences between the treatment and control groups before the treatment.

4.2 Crime

In general, I use the same econometric model defined before with a few variations. I use the following reduced-form specification:

$$Crime_{bt} = \beta * PostUVA_t * Close_b + \gamma_b + \gamma_t + \varepsilon_{bt} \tag{3}$$

Where $Crime_{bt}$ is the crime outcome (it means homicides, person, car, motorcycle, and residence thefts and domestic violence), in neighborhood b at time t. $PostUVA_t$ is an indicator variable taking value 1 for all years after the cultural center opening and $Close_b$ is an indicator variable taking value 1 for the neighborhoods close to centers, and 0 otherwise. $PostUVA_{bt}$ and $Close_b$ are always 0 for never treated neighborhood. γ_b and γ_t are neighborhood and year fixed effects, which absorb fixed differences across neighborhoods and across years. Errors ε_{bt} are clustered to the neighborhood level.

The coefficient of interest in Equation (3) is β and it measures the change in the outcome variables of the neighborhoods close to centers compared to neighborhoods far to the centers, conditional on the set of neighborhood and year fixed effects.

It is important to mention that in some of the cultural centers there were also coexistence councils. These councils brought the community together with the local police. This dynamic may be generating that now the cost of presenting legal action decreases, in this case, my estimate is a lower bound of the true effect of the cultural center program on crime results.

In this specification, I cannot include or test differences for control variables. Because there are no measurements at this level of aggregation that can be used to check if there are differences before treatment that may be affecting the results of the crime outcomes. However, the inclusion of neighborhood and time fixed effects can capture the greatest amount of bias and allow me to identify the causal effect of cultural centers on crimes.

Note that as I explained in the Data section, I create the buffers around the centers and then intersect them with the neighborhoods. This generates that sometimes the largest neighborhoods are not fully included in the buffers. What it means, some neighborhoods are not completely treated depending on the specification. I try to solve this problem using the neighborhood's total area and the intersected area. I use the below Equation:

$$Crime_{bt} = \frac{PerAreab_b}{Areat_b} * Crimes_{bt}$$

First, I calculate $PerAreab_b$, which is the percentage of the neighborhood area that remains in the buffer. Second, I only assign that percentage to neighborhood crimes, $Crimes_{bt}$. Third, the crimes assigned are divided between the total area of the treated neighborhood $Areat_b$.

As usual, I should use crimes by inhabitants. However, as explained above, there is no data at the neighborhood level. For this reason, I use $Crime_{bt}$ in units per neighborhood kilometer. These modifications are subject to the assumption that crimes are distributed evenly throughout the extent of neighborhoods. This is probably not true since it is common to find crime hot spots. But given the limitations in georeferenced data in more detail, this is the best I can do to avoid bias.

I also estimate the dynamic version of the Equation (2), only with the modification of crime outcomes. This specification again allows me to see the evolution of the effect of cultural centers on crime outcomes and to test the assumption of parallel trends.

5 Results

In this section, I describe the main findings of the effect of the centers on education and crime outcomes. I also discuss some of the ways that can explain those results and their implications over the communities' wellness.

5.1 Education

Table 2 presents the results of estimating Equation (1) with the test scores as variables in standardized values. Columns 1, 2 and 3 of the table present the results for language and columns 3, 4 and 5 present the results for math. In every section, the first and second columns include no controls and the third column includes control variables. Since I lose some observations when I include controls, the second column of every section presents the results for the sample that also has control variables, while the first column presents the results for the complete sample.

Table 2: Results all tests

	Language			Math		
	(1)	(2)	(3)	(4)	(5)	(6)
PostUVA	0.12***	0.15***	0.10***	0.12***	0.13***	0.096***
	(0.026)	(0.032)	(0.030)	(0.026)	(0.031)	(0.030)
Controls	No	No	Yes	No	No	Yes
Avg Non-Standar. Var.	253.61	263.57	263.57	237.51	246.96	246.96
SD Non-Standar. Var.	127.10	126.56	126.56	127.10	127.07	127.07
Schools	718	493	493	715	491	491
Observations	12,949	9,644	9,644	13,435	9,990	9,990
Adjusted R^2	0.71	0.71	0.72	0.71	0.73	0.73

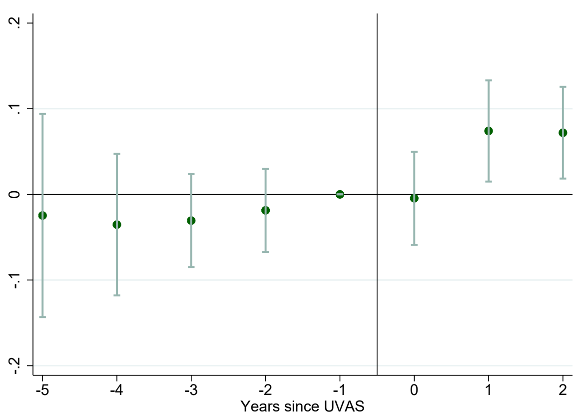
Notes: All specifications include school and year fixed effects. Controls are the number of students enrolled, the number of teachers and staff by gender. Robust standard errors are clustered at the school level and are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The first and second Columns of both language and math sections show that controlling for school and time fixed effects, after the implementation of the cultural centers, schools near to the centers improve their results in Saber test scores. In particular, a school near to centers obtain around 0.12 standard deviations more in both language and math tests. Although the coefficients decrease a little, the third column of the two sections shows that these effects remain at the inclusion of control variables, with effects of 0.10 standard deviations more for both tests.

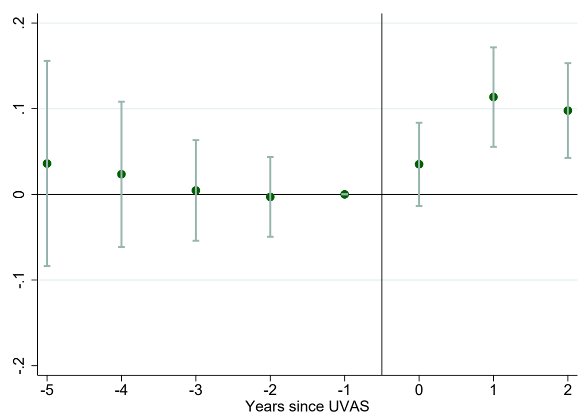
Table B.3 presents results of this specification disaggregated by test. Panel 1, 2, 3 and 4 present the results for the Saber 3, 5, 9 and 11 tests, respectively. I find that the effect reported in Table 2 is being driven by improving the results of the Saber tests for grades 3, 5 and 9. While no effects are found for test results in Saber 11. It is also interesting to comment that results are substantially higher in tests 3 and 5. Which would indicate that cultural centers are mostly affecting younger children.

To explore the dynamic effect of the construction of cultural centers on education outcomes, Figure 4 illustrates the results of the estimating Equation (2). The left panel presents the results for language and the right panel presents the results for mathematics in a window of 5 years before and 2 years after the center opening year. This graph provides evidence of parallel trends before the implementation of the centers. Since the coefficients are not significant for any of the years before the time of opening of cultural centers. I can also observe the positive and significant effect on both tests in years 1 and 2 following the policy. This effect is in line with that of the table 2 where the magnitude of the coefficients at approximately 0.10 standard deviations in both years.

Figure 4: Coefficients all tests



(a) Math



(b) Language

Notes: This figure reports the dynamic coefficients obtained from the estimation of Equation (2) together with 95% confidence intervals. The sample covers the window 5 years before and 2 years after the center opening year. Panel A reports coefficients for the Math test. Panel B reports coefficients for the Language test.

I also present these graphs for each Saber test in Figure B.4. I find trajectories similar to those in Figure 4 for test scores in Saber 3, 5 and 9 in both math and language tests. However, the coefficients are slightly larger, going to approximately 0.15 standard deviations more for schools close to the centers. On the other hand, there is no evidence of effects for the Saber 11 test.

Table 3 shows the coefficients for the specification (1) using the other approved, dropouts and transfers rate outcomes. Panel 1 presents results for the primary level, while panels 2 and 3 present the results for secondary and media education levels, respectively. Columns 1 and 2 of each section presents results for women for specifications with and without controls, respectively. While columns 3 and 4 present results for men of these same specifications.

I find that there is no class composition effect for the primary level since the coefficients are not significant for the 3 variables of interest in any of the specifications for both groups, women, and men. This would indicate that effects found for Saber 3 and 5 tests reported in panels 1 and 2 of Table B.3 are not being guided by a class composition effect.

Concerning Panel 2, which corresponds to the secondary level, negative results for the approved rate and positive for the dropout rate for all specifications in both groups are observed, while no significant results are found for the transfer rate. This would indicate that the effects found for the Saber 9 tests might be guided by this change in the composition of the courses. However, when the dynamic effect is realized for these outcomes, coefficients reported in Figure C.6, it is observed that this effect is very small and does not become significant for any of the years after the implementation of the centers.

Probably, for 9^{th}-grade students, a class re-composition effect is presented. It is also important to mention that this effect is contrary to expectations. Since according to Panel 2 of the Table 3, after the implementation of the cultural centers, schools close to these levels decrease their approval rate for both boys and girls by 0.12 standard deviations. Besides, it is also found that the dropout rate is increased by 0.10 standard deviations.

Table 3: Results other outcomes

	Approved				Dropouts				Transferred			
	Women		Men		Women		Men		Women		Men	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Primary											
PostUVA	0.0024	-0.041	-0.016	-0.12**	0.065	0.043	0.096	0.077	0.012	0.024	0.024	0.13**
	(0.051)	(0.056)	(0.045)	(0.049)	(0.069)	(0.077)	(0.066)	(0.073)	(0.060)	(0.068)	(0.054)	(0.062)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Avg Non-Standar. Var.	0.90	0.89	0.89	0.88	0.03	0.02	0.03	0.03	0.05	0.06	0.05	0.06
SD Non-Standar. Var.	0.12	0.12	0.14	0.13	0.06	0.05	0.07	0.06	0.09	0.09	0.09	0.08
Schools	1,279	790	1,236	749	1,279	790	1,236	749	1,279	790	1,236	749
Observations	6,566	4,219	6,318	3,978	6,564	4,219	6,316	3,978	6,563	4,219	6,315	3,978
Adjusted R^2	0.40	0.33	0.45	0.36	0.30	0.22	0.35	0.26	0.30	0.22	0.33	0.22
	Secondary											
PostUVA	-0.042	-0.11**	-0.085**	-0.12***	0.078*	0.099*	0.099**	0.11*	0.0077	0.041	0.058	0.088*
	(0.044)	(0.050)	(0.040)	(0.046)	(0.045)	(0.060)	(0.044)	(0.063)	(0.050)	(0.054)	(0.044)	(0.051)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Avg Non-Standar. Var.	0.85	0.85	0.82	0.81	0.02	0.02	0.03	0.03	0.06	0.06	0.07	0.07
SD Non-Standar. Var.	0.11	0.11	0.13	0.14	0.04	0.04	0.04	0.05	0.06	0.06	0.06	0.06
Schools	858	538	811	501	858	538	811	501	858	538	811	501
Observations	4,058	2,789	3,784	2,559	4,056	2,788	3,782	2,558	4,058	2,789	3,784	2,559
Adjusted R^2	0.52	0.58	0.62	0.66	0.27	0.27	0.31	0.32	0.34	0.38	0.38	0.44
	Media											
PostUVA	-0.13**	-0.095	-0.14**	-0.11*	0.031	0.017	0.082	0.075	0.077	0.055	0.085	0.068
	(0.055)	(0.058)	(0.055)	(0.060)	(0.051)	(0.055)	(0.059)	(0.069)	(0.052)	(0.051)	(0.062)	(0.061)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Avg Non-Standar. Var.	0.84	0.84	0.78	0.78	0.02	0.02	0.03	0.03	0.06	0.06	0.07	0.07
SD Non-Standar. Var.	0.13	0.12	0.14	0.14	0.04	0.03	0.04	0.04	0.06	0.06	0.07	0.07
Schools	594	475	551	436	594	475	551	436	594	475	551	436
Observations	3,251	2,779	2,980	2,526	3,251	2,779	2,980	2,526	3,251	2,779	2,980	2,526
Adjusted R^2	0.60	0.62	0.60	0.60	0.37	0.40	0.35	0.35	0.38	0.42	0.32	0.34

Notes: All specifications include school and year fixed effects. Controls are the number of students enrolled, the number of teachers and staff by gender. Robust standard errors are clustered at the school level and are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Initially, I made this specification differentiated by gender to be able to separate the cultural and sports effects of the centers. Since it is common for boys to be more interested in sports and girls for cultural issues. However, as Table 3 shows this distinction does not seem to exist, giving indications that children did not self-select by gender in any of the services offered by the centers.

Panel B of Figures C.5 to C.7 can give more clarity about this. Here it can be seen that coefficients for three educational levels are almost equal for both groups, women, and men. Having the same magnitude and the same level of significance through the outcomes and educational levels.

5.2 Crime

Table 4 reports the coefficients of estimating specification (3), for crime outcomes. The dependent variables are homicides, car, motorcycle, person and residence thefts and domestic violence in columns 1 to 6, respectively.

Table 4: Results Crime

	Homicides	Car thefts	Motorcycle thefts	Thefts	Residence thefts	Domestic violence
	(1)	(2)	(3)	(4)	(5)	(6)
PostUVA	0.026	-0.095	-0.12***	0.059	-0.12*	-0.022
	(0.062)	(0.060)	(0.040)	(0.13)	(0.069)	(0.034)
Avg Non-Standar. Var.	0.01	0.02	0.05	0.09	0.02	0.07
SD Non-Standar. Var.	0.02	0.03	0.08	0.20	0.03	0.77
Neighborhoods	326	349	421	437	379	372
Observations	1,322	1,542	2,128	2,240	1,586	1,632
Adjusted R^2	0.67	0.60	0.78	0.58	0.62	0.51

Notes: All specifications include school and year fixed effects. Robust standard errors are clustered at the neighborhood level and are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

I find that there is a general reduction in automobile thefts. Particularly, there is a reduction in car thefts of 0.12 standard deviations to neighborhoods close to cultural centers after their opening. The reduction in motorcycle thefts is similar, at 0.11 standard deviations. There are no statistics sign effects on homicides and robbery of people but their coefficient is positive, which would be contrary to the intuition that neighborhoods with nearby centers improved security indicators. The coefficients of the results of residence thefts and domestic violence are not significant either but the coefficient is negative, which would be in line with what was expected.

The dynamic version proposed in Equation (2) is shown in Figure 5 for crime outcomes. In this case, it is difficult to conclude that before the implementation of the policy there were no differences between the treatment and control group for some specific cases.

Since, the graphs show some coefficients different from zero for the results of homicides, motorcycle and residence thefts. It is cast doubt on parallel trends assumption.

These results show that these cultural centers had great implications in the beneficiary communities that now have a nearby place to spend free time and that in turn perceive it as a safe place. In the next, section I explore some changes in the specification to verify that results remain robust.

5.3 Robustness checks

I implement different exercises to verify whether the main findings are robust to different specifications. In this section, I describe and explain results and changes in specifications.

5.3.1 Other buffers

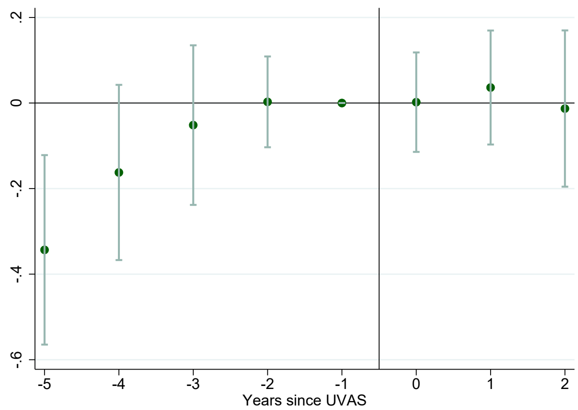
As I indicated in the Econometric Model section, in my main specification I use a 1.5 kilometers buffer around the cultural center and based on this I define the treatment and control group. However, this specification may not be robust, since this distance is chosen based on walking time, this could be generating a bias in my estimate. Since this buffer may be taking people who are not treated or maybe leaving out people who are treated. That is, with this method I may be misidentifying the treatment and control group.

Besides, we could also think that these centers may be generating spillovers on communities that initially do not seem to benefit from this policy. In this case, the effects of the construction of cultural centers would be underestimated.

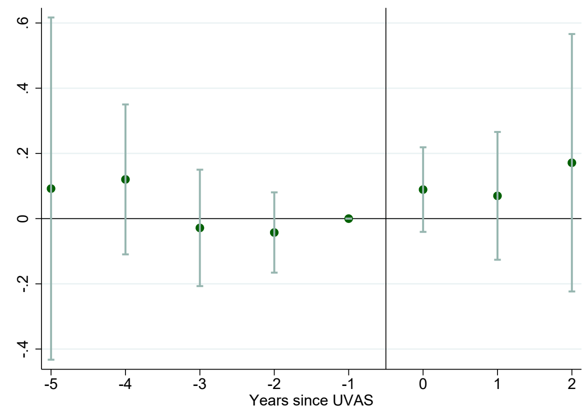
For these reasons, I implement the strategy defined in Equation (1) for buffers of 1, 1.5, 2 and 2.5 kilometers around each center. If the effects I find are consistent with this change in the buffers, I should find stable coefficients through the specifications. I should also note that the effect is less as the increase of the buffer since as the distance to the cultural

Figure 5: Coefficients by crime

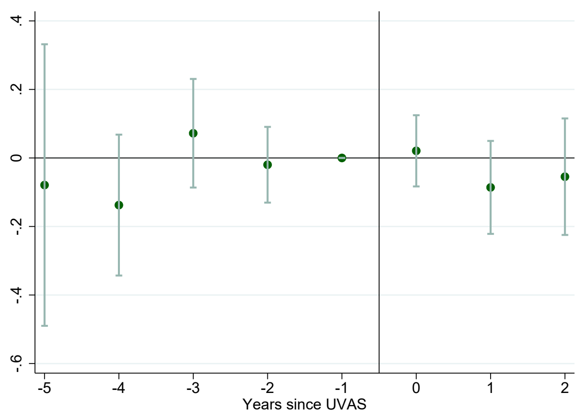
(a) Homicides



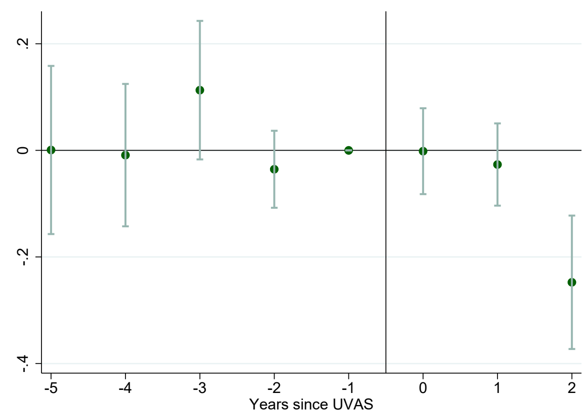
(b) Thefts



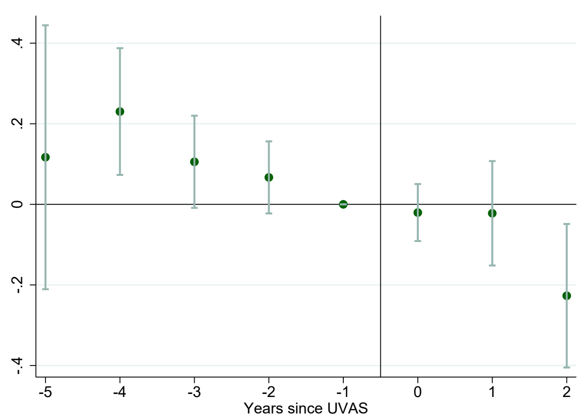
(c) Car thefts



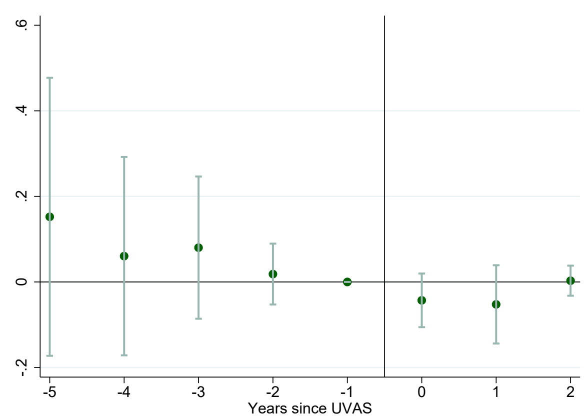
(d) Motorcycle thefts



(e) Residence thefts



(f) Domestic violence



Notes: This figure reports the dynamic coefficients obtained from the estimation of Equation (2) together with 95% confidence intervals. The sample covers the window 5 years before and 2 years after the center opening year. Panels A to F report data on homicides, person, car, motorcycle and residence thefts, and domestic violence.

center increases if my hypothesis is correct, the centers should be used less and therefore the effect would dissipate.

Figure D.8 presents the coefficients β of the dynamic Equation (2) for Saber test scores in math and language for all buffers. This graph shows that coefficients have a similar trajectory for both tests in the time window 5 years before and 2 years after the center opening year. The coefficients are not significant in any of the cases before the opening of the centers, and they are always significant at 1 % after the opening of the centers. The coefficients remain almost equal in the 1 and 1.5km buffers and begin to decrease for the 2 and 2.5km buffers. These results in the specification reject the hypothesis that the results found are due to a bad identification of the treatment and control groups.

On the other hand, Figure D.10 presents the coefficients β of the dynamic Equation (2) for crime outcomes and each buffer. This graph shows that for homicide, car, motorcycle and residence thefts, the coefficients show a similar trajectory during the study period. However, the significance of the coefficients before the opening of the centers varies greatly for homicides and residence thefts, so the existence of parallel trends for these outcomes is not definitive.

Moreover, for the outcomes of thefts and domestic violence the coefficients have a great variation. This seems to indicate that the choice of buffers around the centers is affecting the results found in these outcomes. Therefore I cannot discard that there is a bad identification of the treatment and control groups using this method.

I also did this exercise omitting distant municipalities that have no unit treated. This excludes according to the Tables A.1 and A.2 the municipalities of Barbosa, Girardota, Sabaneta and Caldas. Figure D.9 shows that for educational outcomes the coefficients stabilize much more but there are no implications other than those discussed above.

Regarding crime, Figure D.11 shows that for almost all outcomes the coefficients stabilize and show a similar trajectory throughout the study period, specifically homicides, car, and motorcycle thefts. Concerning the other outcomes, it is not yet clear that there are parallel trends before the implementation of the centers and for subsequent years, the results seem to be zero.

5.3.2 Continuous treatment

In spite of the previous robustness with different buffers, the choice of these can arbitrarily remain not satisfactory. Therefore, I use the following specification:

$$Y_{it} = \beta_1 * (PostUVA_{it} * Continuos_i) + \beta_2 * PostUVA_{it} + \sum_t X_i \alpha_t + \gamma_i + \gamma_t + \varepsilon_{it} \quad (4)$$

Where Y_{it} is the outcome of interest in education or crime, in the analysis unit i (school or neighborhood) at time t. $PostUVA_{it}$ is an indicator variable taking value 1 for all years after the cultural center opening in the units close to centers, and 0 otherwise. $PostUVA_{it}$ is always 0 for never treated units. $Continuos_i$ is the continuous distance of the unit to the nearest center in kilometers. As my main specification, I include controls variables X_i before the treatment interacted with time dummies when i is school. γ_i and γ_t are unit and year fixed effects. Errors ε_{it} are clustered to the unit level.

In the specification (4) the coefficient of interest is β_1 and it measures how the outcome variables affect as the distance to a cultural center increases after the implementation of these. As you can see in this specification, arbitrary buffers are not selected, but the continuous distance of each school or neighborhood to the nearest center is used. To be in accordance with the previous results, this specification should show that farther schools to the centers have a lower performance in the educational outcomes. While neighborhoods farther from the centers have worse indicators of security.

Table 5 reports the coefficients of the specification (4) for Saber test scores. This table shows that there is no significant effect of being far from cultural centers. However, the sign is in line with intuition, indicating that there is a negative relationship between distant schools and their performance in the Saber tests. Also, Table E.4 reports the coefficients of the specification (4) for other education outcomes.

Table 5: Continuous result all tests

	Language			Math		
	(1)	(2)	(3)	(4)	(5)	(6)
Continuos*PostUVA	-0.0050	-0.0034	-0.0028	-0.00075	0.00071	0.0012
	(0.0036)	(0.0038)	(0.0035)	(0.0035)	(0.0036)	(0.0036)
PostUVA	0.063**	0.083**	0.034	0.056*	0.062*	0.026
	(0.030)	(0.035)	(0.033)	(0.031)	(0.036)	(0.035)
Controls	No	No	Yes	No	No	Yes
Avg Non-Standar. Var.	253.61	263.57	263.57	237.51	246.96	246.96
SD Non-Standar. Var.	127.10	126.56	126.56	127.10	127.07	127.07
Schools	718	493	493	715	491	491
Observations	12,949	9,644	9,644	13,435	9,990	9,990
Adjusted R^2	0.70	0.71	0.72	0.71	0.73	0.73

Notes: All specifications include school and year fixed effects. Controls are the number of students enrolled, the number of teachers and staff by gender. Robust standard errors are clustered at the school level and are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Finally, Table 6 reports the coefficients of the specification (4) for crime outcomes. Following Table 4, I find that neighborhoods far from the centers show an increase in the car and motorcycle thefts. On the other hand, this table also shows that using the continuous distance from the neighborhood to the center there is a reduction in personal and residence thefts. This effect is of lesser magnitude and is consistent with the results found in the main specification, where the coefficient for this variable was positive but not significant. Regarding homicides and domestic violence, I do not find significant results in this specification.

5.3.3 Intensity

It can be seen in Figure A.2, it is possible that a treated unit is exposed to the proximity of more than one center. I take advantage of this variation and use the following

Table 6: Continuous result Crime

	Homicides	Car thefts	Motorcycle thefts	Thefts	Residence thefts	Domestic violence
	(1)	(2)	(3)	(4)	(5)	(6)
Continuos*PostUVA	0.012	0.024**	0.013***	-0.026**	-0.039***	-0.0041*
	(0.013)	(0.011)	(0.0048)	(0.011)	(0.012)	(0.0022)
PostUVA	-0.14	-0.10	-0.063*	0.11	0.12	0.12
	(0.089)	(0.069)	(0.034)	(0.11)	(0.097)	(0.12)
Avg Non-Standar. Var.	3.08	4.93	12.83	22.71	3.68	16.08
SD Non-Standar. Var.	3.76	6.60	21.04	95.62	3.90	216.91
Neighborhoods	328	351	423	439	381	374
Observations	1,328	1,551	2,138	2,250	1,594	1,637
Adjusted R^2	0.54	0.69	0.84	0.60	0.47	0.51

Notes: All specifications include school and year fixed effects. Robust standard errors are clustered at the neighborhood level and are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

specification:

$$Y_{it} = \sum_{n-1} \beta_{n-1} * (PostUVA_{it} * Intensity_i) + \sum_t X_i \alpha_t + \gamma_i + \gamma_t + \varepsilon_{it} \tag{5}$$

Where Y_{it} is the outcome of interest in education or crime, in the analysis unit i (school or neighborhood) at time t. $PostUVA_{it}$ is an indicator variable taking value 1 for all years after the cultural center opening in the units close to centers, and 0 otherwise. $PostUVA_{it}$ is always 0 for never treated units. $n-1$ are dummies that represent the number of close centers. $Intensity_i$ is the number of centers to which a unit is nearby using a 1.5 kilometers buffer. As my main specification, I include controls variables X_i before the treatment interacted with time dummies when i is school. γ_i and γ_t are unit and year fixed effects. Errors ε_{it} are clustered to the unit level.

In specification (5) the coefficients of interest are $\sum_{n-1} \beta_{n-1}$ and they measure how the outcome variables change as the number of close cultural centers increases.

As stated in the Context section, the cultural centers have recreation and sports activities, but these vary across the centers. In addition to this, each center has its unique program. Thus, it is expected that schools or neighborhoods near more than one center have access to a more varied offer of cultural and sports services. I should then find larger effects in units exposed to more centers.

Table 7 reports the coefficients of estimating Equation (5) with test scores as the dependent variable. Table reports coefficients for language in the first section and mathematics in the second section. Here the coefficients for schools exposed to the proximity of up to 4 cultural centers are reported. It is also interesting to note that for those schools exposed to two cultural centers the effect is almost double that found in Table 2. Also, Table E.5 reports the coefficients of the specification (5) for rates of approved, dropout and transferred.

Table 7: Intensity results all tests

	Language			Math		
	(1)	(2)	(3)	(4)	(5)	(6)
1 UVA	0.066**	0.070*	0.051*	0.046*	0.046	0.025
	(0.030)	(0.038)	(0.030)	(0.028)	(0.034)	(0.030)
2 UVAs	0.21***	0.24***	0.17**	0.24***	0.25***	0.20***
	(0.060)	(0.072)	(0.073)	(0.055)	(0.066)	(0.067)
3 UVAs	0.17***	0.22***	0.15***	0.16***	0.20***	0.15**
	(0.042)	(0.053)	(0.051)	(0.054)	(0.063)	(0.062)
4 UVAs	0.18**	0.28***	0.27***	0.14*	0.16*	0.18*
	(0.079)	(0.043)	(0.057)	(0.079)	(0.084)	(0.10)
Controls	No	No	Yes	No	No	Yes
Avg Non-Standar. Var.	253.61	263.57	263.57	237.51	246.96	246.96
SD Non-Standar. Var.	127.10	126.56	126.56	127.10	127.07	127.07
Schools	718	493	493	715	491	491
Observations	12,949	9,644	9,644	13,435	9,990	9,990
Adjusted R^2	0.71	0.71	0.72	0.71	0.73	0.73

Notes: All specifications include school and year fixed effects. Controls are the number of students enrolled, the number of teachers and staff by gender. Robust standard errors are clustered at the school level and are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The proposed intuition is also ratified by analyzing the coefficients of the schools exposed to only one cultural center since these are of much less magnitude and with less significance. Even the coefficient for the math test with the inclusion of controls becomes not significant.

Finally, Table 8 reports the coefficients of the specification (5) for crime outcomes. This table presents the coefficients for neighborhoods exposed to up to 6 nearby centers. Following the results found in Table 4, I find that the biggest decrease in car and motorcycle thefts is in neighborhoods near to 3 cultural centers. However, for car thefts, the coefficient changes sign and becomes significant for those neighborhoods close to 5 centers. This indicates that these neighborhoods had increases in the theft of cars after the implementation of the centers.

Table 8: Intensity results Crime

	Homicides	Car thefts	Motorcycle thefts	Thefts	Residence thefts	Domestic violence
	(1)	(2)	(3)	(4)	(5)	(6)
1 UVA	0.076	-0.12*	-0.10	0.35	-0.078	-0.0064
	(0.087)	(0.071)	(0.065)	(0.29)	(0.10)	(0.024)
2 UVAs	0.041	-0.062	-0.11*	-0.075	-0.12	-0.034
	(0.084)	(0.085)	(0.062)	(0.11)	(0.084)	(0.037)
3 UVAs	-0.093	-0.37**	-0.26***	-0.15*	-0.19**	-0.029
	(0.14)	(0.18)	(0.076)	(0.087)	(0.090)	(0.050)
4 UVAs	-0.074	0.17	0.026	-0.24***	-0.17**	-0.022
	(0.11)	(0.12)	(0.047)	(0.075)	(0.081)	(0.041)
5 UVAs	0.20*	0.18***	-0.14*	-0.27***	-0.15***	-0.051
	(0.10)	(0.064)	(0.085)	(0.067)	(0.048)	(0.060)
6 UVAs	0.37***		-0.14***	-0.28***	-0.10**	-0.076
	(0.052)		(0.025)	(0.044)	(0.050)	(0.067)
Avg Non-Standar. Var.	0.01	0.02	0.05	0.09	0.02	0.07
SD Non-Standar. Var.	0.02	0.03	0.08	0.20	0.03	0.77
Neighborhoods	326	349	421	437	379	372
Observations	1,322	1,542	2,128	2,240	1,586	1,632
Adjusted R^2	0.67	0.61	0.78	0.59	0.62	0.51

Notes: All specifications include school and year fixed effects. Robust standard errors are clustered at the neighborhood level and are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Regarding the other crime outcomes, I find a decrease in person and residence thefts for exposed neighborhoods from 3 to 6 centers. For homicides, I find that there is a positive effect, that is, an increase in homicides for those neighborhoods exposed to 5 and 6 centers, this effect being greater for the exposure of 6. Despite having a negative meaning in all coefficients, I do not find the effects on domestic violence.

These results show that there is an increase in the well-being of the communities in terms of increases in security and that these effects increase as a unit is exposed to a greater number of neighborhoods. These effects are evidenced in the outcomes of motorcycle and residence thefts. However, it is not so clear for homicides and car thefts because the coefficient changes sign indicating an increase for those neighborhoods exposed to a significant number of centers.

6 Discussion

So far, we see that the construction of these cultural centers had direct and positive implications on educational and crime outcomes. The dimensions of the results about crime are in line with others results that evaluate similar policies (Blattman et al. (2017) Ferraz et al. (2016) and Mihinjac & Saville (2019)). However, in terms of education, I find that this policy was more effective than others that even with similar policies do not find effects or are very low (Borkum et al. (2012), De Witte & Geys (2011) and Rodríguez-Lesmes et al. (2014). Below I discuss the possible ways for which this policy is being effective in terms of both crime and education outcomes.

First, the construction of the centers had a great reception by the communities since they felt included and heard by the policymakers. This generates, that they manifest the deficiencies that arose in their sectors and use the services offered by cultural centers. On the one hand, schools close to these centers take advantage of these places to teach their sport and computer classes more dynamically. On the other hand, those young people who do not have access to the Internet are also using the computer rooms offered to carry out their homework.

These places also became a family gathering center, where children will make use of the activities offered while parents enjoy the well-being that centers provide for the outdoor environment. Besides, certified courses for mothers are also developed. Overall, these places bring benefits for each family member. As indicated above, the benefited families have low resources that otherwise cannot access recreation and expansion services.

However, I cannot distinguish the effect of each course or the benefits that come with only the construction of the center itself and family time. What can be said is that culture centers and their services make children present better results in their Saber tests. Also, the intensive use of these cultural centers can only be verified anecdotally, as I do not have a record of visits to the centers.

Second, the construction of the centers did improve the sense of security of the inhabitants of these areas. Due to the great investment in security and lighting, places that were once dark places and conducive to deeds such as theft and murder, are now places full of light and people enjoying the place. In addition, this investment brought effects in the neighborhood in general that now became more attractive to families. I can only test the change in the composition through the results at the school level. That is, families with children do not seem to have a compositional effect. Nevertheless, I cannot say anything about those families without children. There may be a change in the composition of people living in the neighborhood that I am not able to capture. However, it does not make much sense for families without children to change their residence to exploit the services of the centers that are mostly for children. If this composition effect is being presented, its size must be very low.

7 Conclusions

This paper provides evidence of the effect of the provision of public goods on education and crime outcomes. I evaluate the effect of the implementation of cultural centers in disadvantaged communities of Medellin. Interesting, this policy was implemented with the intervention of the benefited communities. Literature, in general, finds that this type of investment improves the well-being of the favored communities across different fields. I choose education and crime because of the type of services offered by these centers. Each cultural center necessarily offered a sports component and a cultural component. Both factors can affect the educational outcomes of children who otherwise could not access this type of services. Moreover, this same mechanism may be affecting criminality since it is now more profitable for children to study than to commit crimes, given their positive results. Besides, another factor that can affect the criminality of neighborhoods is the investment in security and lighting that the construction of the centers entailed.

I use the distance from schools and neighborhoods to the nearest center to identify treatment and control groups. Then, I use a dynamic difference in differences strategy, since the opening of the cultural centers was carried out in different years from 2014.

The findings indicate that schools close to the centers obtained an increase of 0.10 standard deviations in the results of language and mathematics, after the implementation of the centers. These findings are being driven by the increased performance of the youngest students, that is, students in 3^{rd} and 5^{th} grades. In addition to this, I verify that the implementation of the centers is not causing a re-composition effect in the classes, that is, to encourage the migration of students. Concerning crime, I find that neighborhoods close to cultural centers obtained a reduction in motorcycle and car thefts by 0.11 standard deviations. In terms of magnitude, the results on crime outcomes are in line with those found in evaluations of other types of policies. With regard to education, this policy shows more effective results than other similar interventions where there are no or very low effects on the test scores.

My results are robust to changes in the specification and other exercises with continuous distance and with the intensity of the treatment that refers to the number of centers to which a unit is nearby.

To conclude, this paper has immediate policy implications for local governments. Since there has been an effort to study what kind of policies have effects on student performance, especially for those underprivileged children. This paper shows that policies focused on disadvantaged populations that participate in the design of these, exposing their true needs have direct implications on the welfare of communities, in terms of education and crime.

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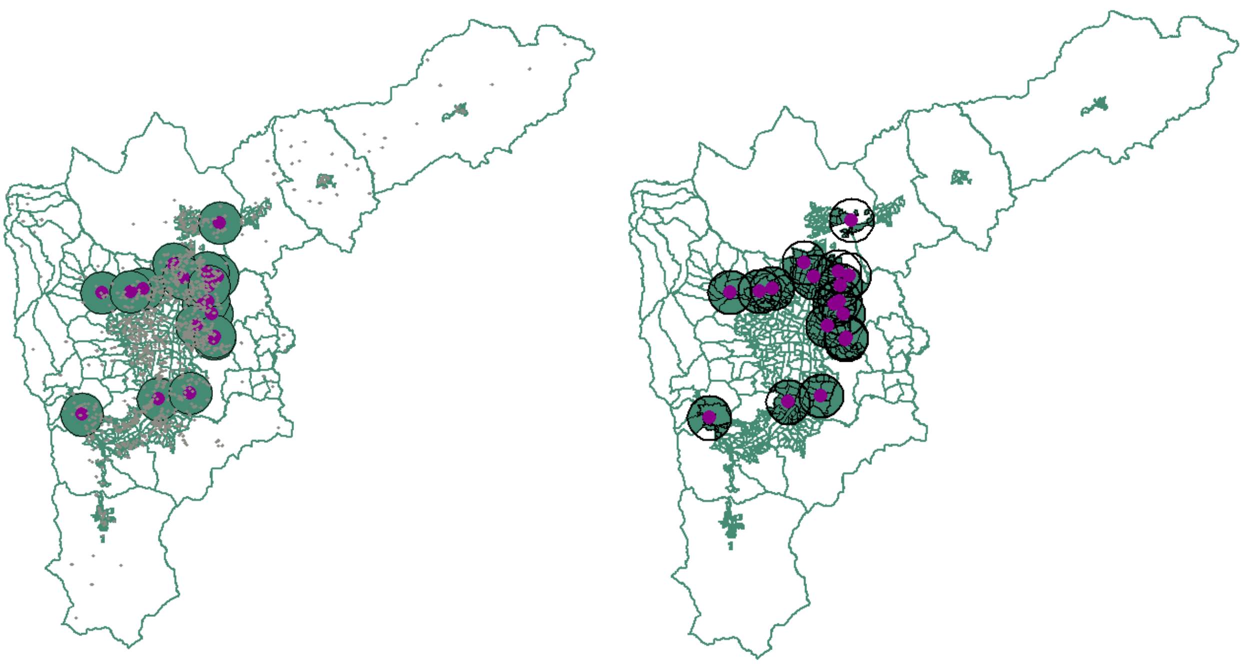
Appendix A Other tables and graphics

Figure A.1: UVAs in Medellín

(a) Before (b) After

Source: EPM
Notes: This figure shows on the left EPM water tanks and on the right a finished and functioning cultural center.

Figure A.2: Culture centers in M.A of Medellín



(a) Schools (b) Neighborhoods

Notes: M.A of Medellín includes the municipalities: Barbosa, Girardota, Copacabana, Bello, Medellín, Itaguí, Envigado, Sabaneta, La Estrella and Caldas. On the left, gray points are schools. On the right, in green neighborhoods treated. Purple points are cultural centers in both graphs.

Table A.1: Distances from schools by municipality

	Obs.	Mean	Min	Max	Treat	Control
Medellín	8168	1716.61	83.89	22182.24	5074	3094
Bello	1491	2382.33	611.09	54340.50	399	1092
Itagui	881	2663.70	26.35	4020.86	174	707
Envigado	689	3272.61	990.68	8920.30	48	641
La Estrella	398	3287.32	1155.52	6763.65	23	375
Copacabana	339	3854.52	739.42	6924.38	21	318
Sabaneta	337	4850.57	3649.36	5973.67	0	337
Girardota	247	11457.67	10144.66	23545.95	0	247
Caldas	233	10241.65	7604.27	14127.98	0	233
Barbosa	223	23580.58	15258.53	49697.23	0	223
Total	13006	2837.10	26.35	54340.50	5739	7267

Notes: This table shows descriptive statistics of the distance in meters from schools to cultural centers by the municipality. Treat and control columns are measured using a 1.5km buffer.

Table A.2: Distances from neighborhoods by municipality

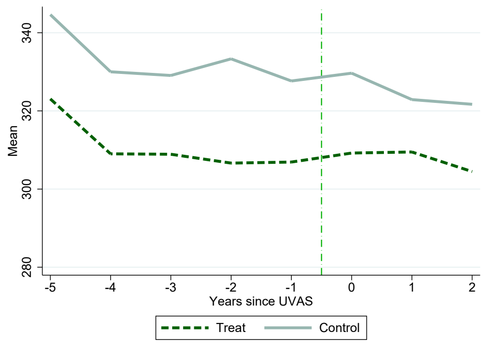
	Obs.	Mean	Min	Max	Treat	Control
Medellín	1272	1405.18	0.00	4876.88	804	468
Bello	375	2151.23	595.14	3778.21	114	261
Itagui	297	2445.00	0.00	3956.07	54	243
Envigado	215	2173.86	520.40	3661.79	54	161
Copacabana	120	2779.17	420.13	4578.47	18	102
La Estrella	27	2782.61	1368.92	6232.48	6	21
Caldas	115	9435.26	7486.37	11525.69	0	115
Barbosa	62	24793.74	23153.37	25381.67	0	62
Sabaneta	56	4552.27	3592.33	4993.83	0	56
Girardota	49	10514.75	9772.61	11074.91	0	49
Total	2588	2932.26	0.00	25381.67	1050	1538

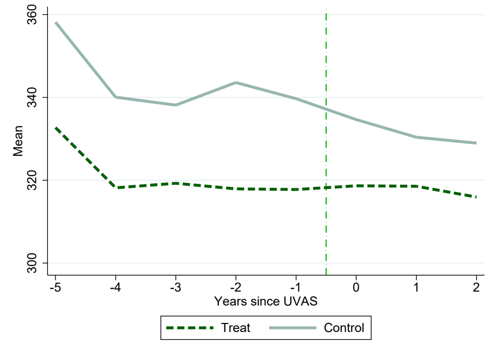
Notes: This table shows descriptive statistics of the distance in meters from neighborhoods to cultural centers by the municipality. Treat and control columns are measured using a 1.5km buffer.

Appendix B Saber

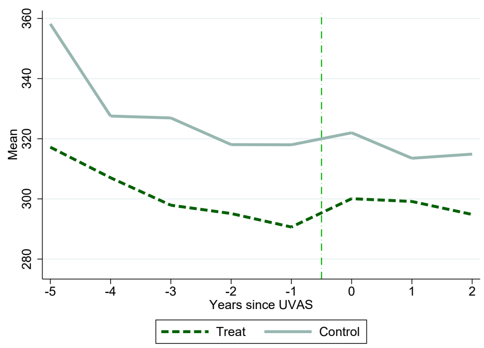
Figure B.3: Raw data by test

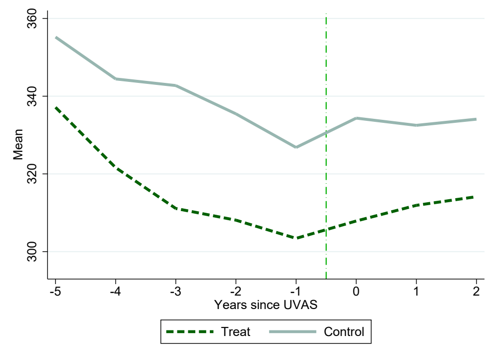
Saber 3



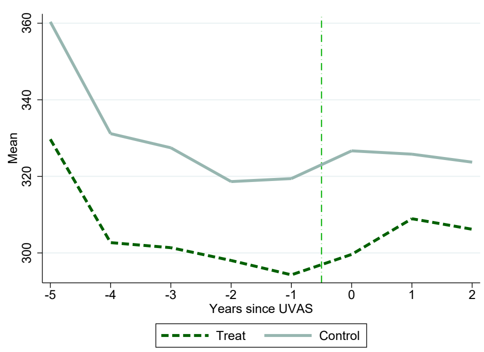


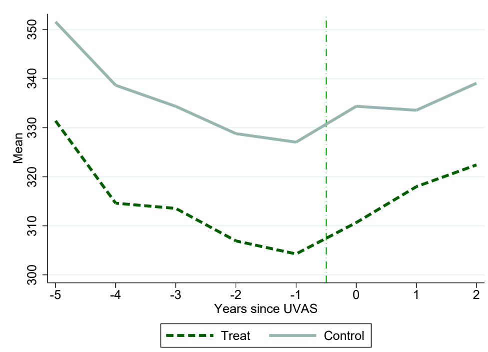
Saber 5



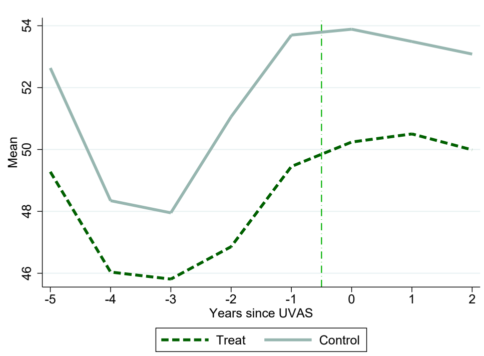


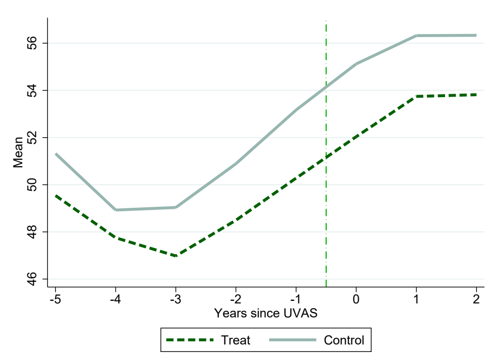
Saber 9





Saber 11





(a) Math

(b) Language

Source: ICFES

Notes: This figure shows raw data by Saber test scores for treated and control groups. Data covers the window 5 years before and 2 years after the center opening year. Column A reports data on Math test score. Column B reports data on Language test score. Solid line represents control group and dotted line represents treat group.

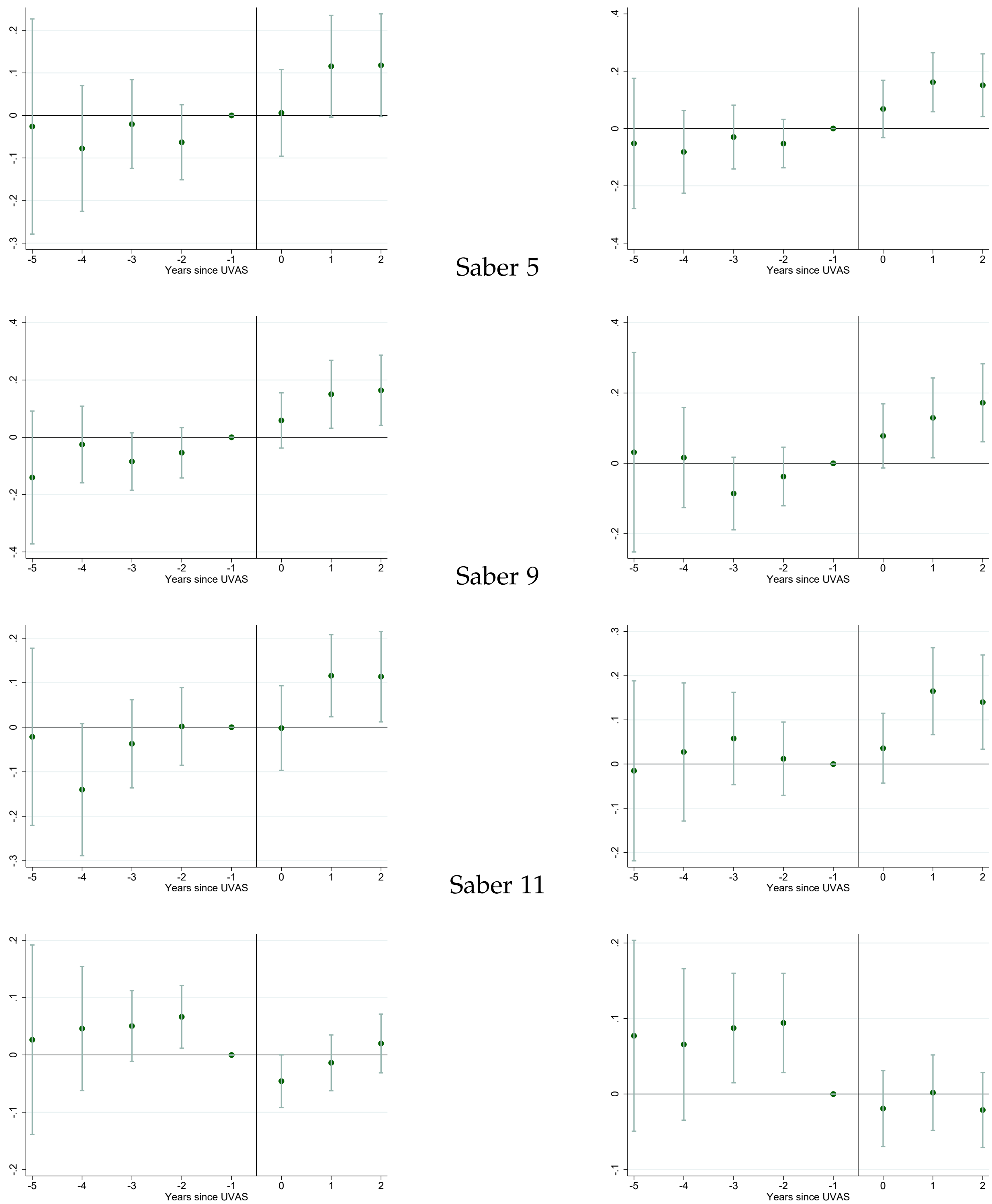
Table B.3: Results by test

	Language			Math		
	(1)	(2)	(3)	(4)	(5)	(6)
			Saber 3			
PostUVA	0.19***	0.20***	0.15**	0.18***	0.17***	0.13**
	(0.050)	(0.060)	(0.059)	(0.052)	(0.059)	(0.059)
Controls	No	No	Yes	No	No	Yes
Avg Non-Standar. Var.	328.94	333.41	333.41	319.49	323.51	323.51
SD Non-Standar. Var.	44.81	47.10	47.10	44.78	46.67	46.67
Schools	598	457	457	600	459	459
Observations	3,214	2,484	2,484	3,209	2,478	2,478
Adjusted R^2	0.71	0.72	0.73	0.69	0.71	0.72
			Saber 5			
PostUVA	0.16***	0.19***	0.15***	0.20***	0.19***	0.16**
	(0.048)	(0.058)	(0.057)	(0.052)	(0.062)	(0.062)
Controls	No	No	Yes	No	No	Yes
Avg Non-Standar. Var.	324.52	329.65	329.65	310.52	315.10	315.10
SD Non-Standar. Var.	47.75	49.87	49.87	46.69	48.81	48.81
Schools	593	455	455	595	455	455
Observations	3,216	2,500	2,500	3,224	2,503	2,503
Adjusted R^2	0.76	0.77	0.78	0.73	0.75	0.76
			Saber 9			
PostUVA	0.17***	0.16***	0.094**	0.15***	0.15***	0.11***
	(0.041)	(0.043)	(0.040)	(0.041)	(0.038)	(0.036)
Controls	No	No	Yes	No	No	Yes
Avg Non-Standar. Var.	323.99	326.72	326.72	314.69	317.28	317.28
SD Non-Standar. Var.	48.70	48.60	48.60	54.40	54.35	54.35
Schools	539	480	480	539	480	480
Observations	2,958	2,697	2,697	2,941	2,681	2,681
Adjusted R^2	0.79	0.79	0.81	0.80	0.82	0.83
			Saber 11			
PostUVA	-0.051*	0.0057	0.019	0.0011	0.058*	0.056*
	(0.027)	(0.028)	(0.027)	(0.029)	(0.031)	(0.031)
Controls	No	No	Yes	No	No	Yes
Avg Non-Standar. Var.	52.45	53.37	53.37	50.51	51.71	51.71
SD Non-Standar. Var.	5.84	5.72	5.72	7.29	7.18	7.18
Schools	600	449	449	600	449	449
Observations	3,403	2,682	2,682	3,914	3,112	3,112
Adjusted R^2	0.90	0.90	0.91	0.89	0.90	0.90

Notes: All specifications include school and year fixed effects. Controls are the number of students enrolled, the number of teachers and staff by gender. Robust standard errors are clustered at the school level and are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure B.4: Coefficients by test

Saber 3



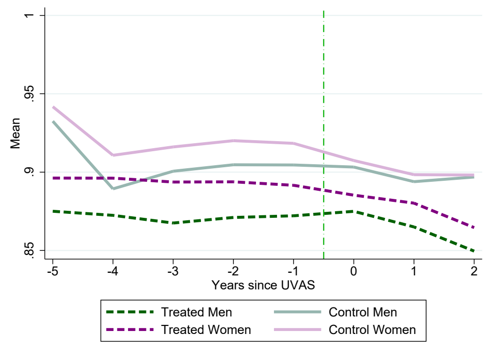
(a) Math (b) Language

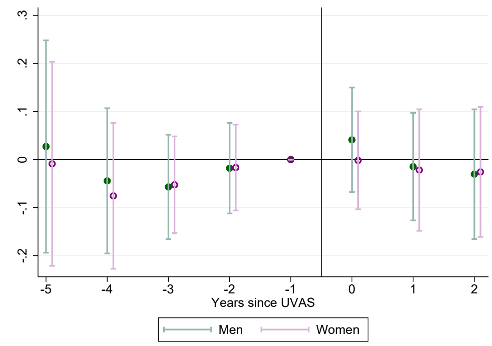
Notes: This figure reports the dynamic coefficients obtained from the estimation of Equation (2) together with 95% confidence intervals. The sample covers the window 5 years before and 2 years after the center opening year. Column A reports coefficients for the Math test. Column B reports coefficients for the Language test. Panels 1, 2, 3 y 4 represent data for Saber 3, 5,9 y 11, respectively.

Appendix C Others outcomes

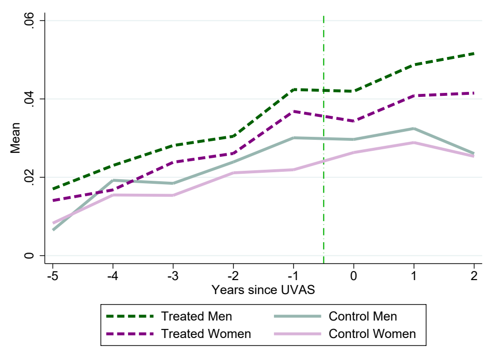
Figure C.5: Raw data and coefficients by primary level

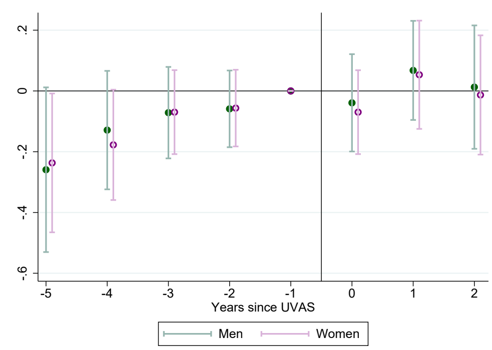
Approved





Dropouts





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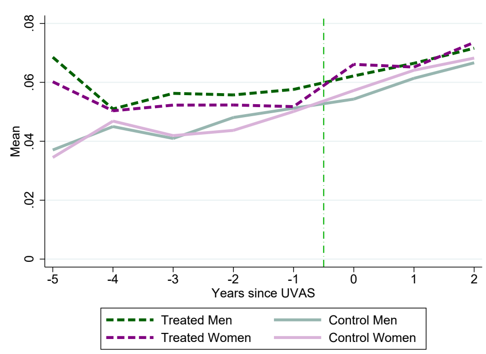
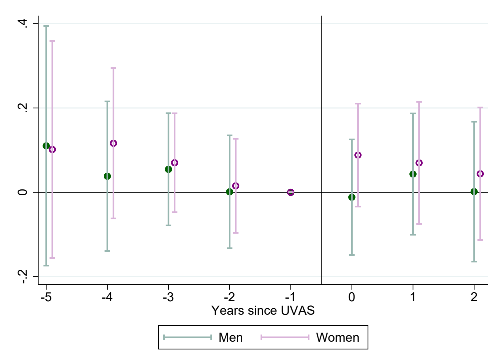


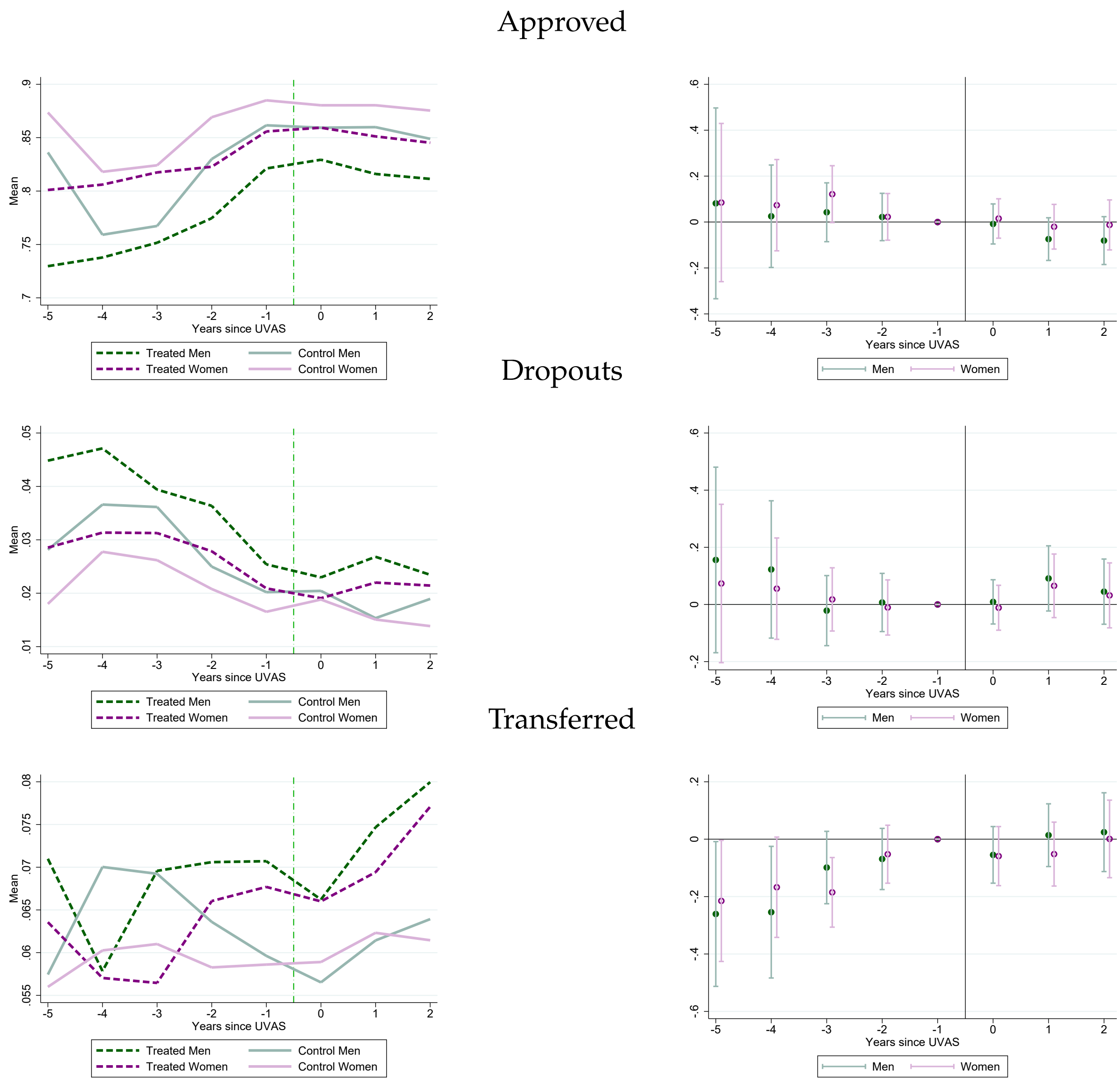


(a) Raw data (b) Coefficients

Source: C600

Notes: This figure shows in Column 1 raw data of other educational outcomes by the primary level for treated and control groups. In Column 2, this figure reports the dynamic coefficients obtained from the estimation of Equation (2) together with 95% confidence intervals. Data covers the window 5 years before and 2 years after the center opening year. Panel 1, 2 y 3 represent data for approved, dropouts and transferred rates. Every graph is divided by gender, purple represents women data and green represents men's data.

Figure C.6: Raw data and coefficients by secondary level



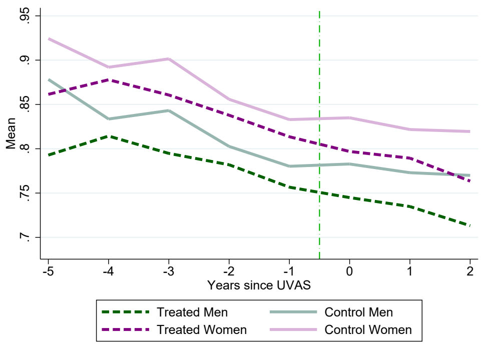
(a) Raw data

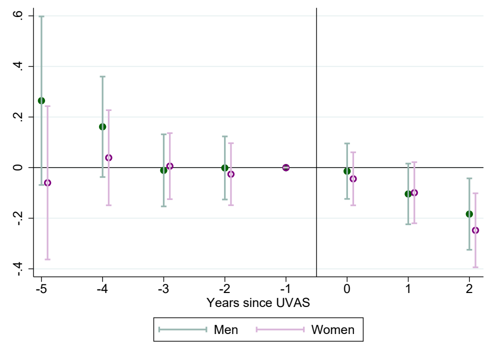
(b) Coefficients

Source: C600
Notes: This figure shows in Column 1 raw data of other educational outcomes by secondary level for treated and control groups. In Column 2, this figure reports the dynamic coefficients obtained from the estimation of Equation (2) together with 95% confidence intervals. Data covers the window 5 years before and 2 years after the center opening year. Panel 1, 2 y 3 represent data for approved, dropouts and transferred rates. Every graph is divided by gender, purple represents women data and green represents men's data.

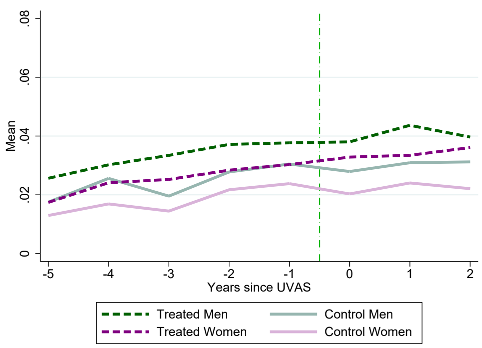
Figure C.7: Raw data and coefficients by media level

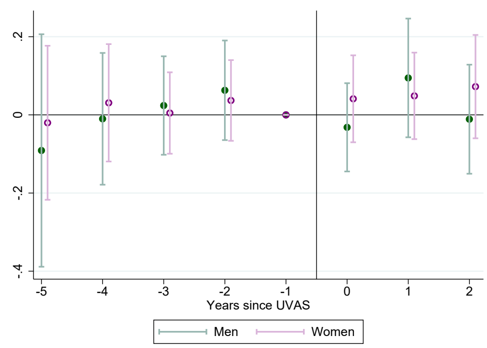
Approved





Dropouts





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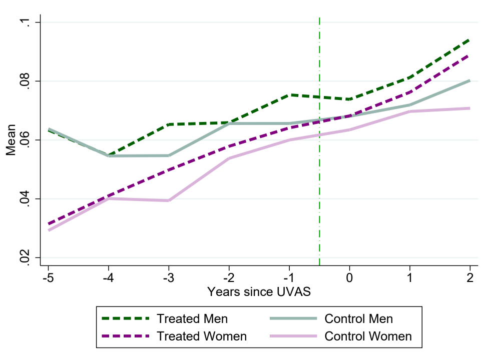
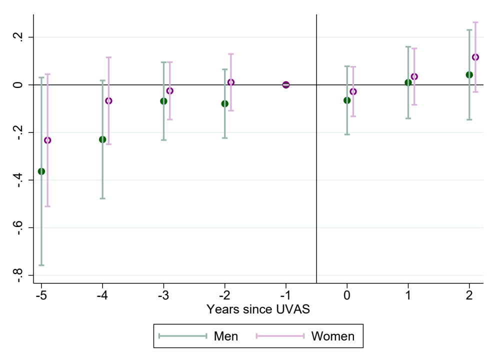




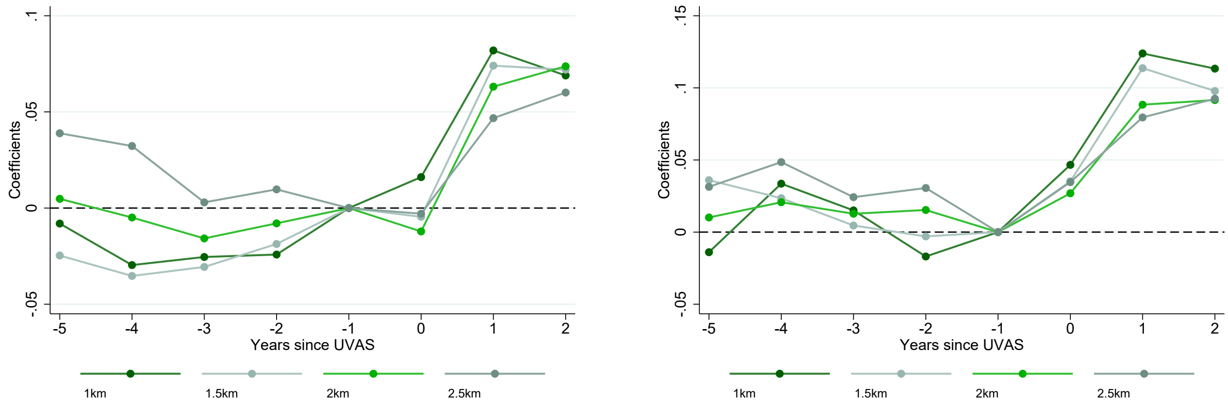
(a) Raw data

(b) Coefficients

Source: C600
Notes: This figure shows in Column 1 raw data of other educational outcomes by media level for treated and control groups. In Column 2, this figure reports the dynamic coefficients obtained from the estimation of Equation (2) together with 95% confidence intervals. Data covers the window 5 years before and 2 years after the center opening year. Panel 1, 2 y 3 represent data for approved, dropouts and transferred rates. Every graph is divided by gender, purple represents women data and green represents men's data.

Appendix D Other buffers

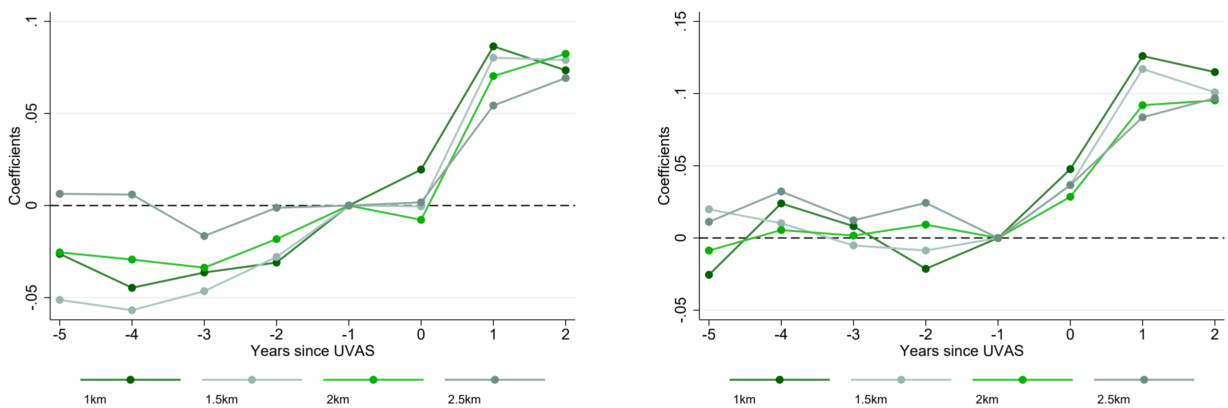
Figure D.8: All tests



(a) Math (b) Language

Notes: This figure reports the dynamic coefficients obtained from the estimation of Equation (2). The sample covers the window 5 years before and 2 years after the center opening year. Panel A reports coefficients for the Math test. Panel B reports coefficients for the Language test. Figure reports coefficients for 1, 1.5, 2 and 2,5 buffers around the centers.

Figure D.9: All tests without distance municipalities

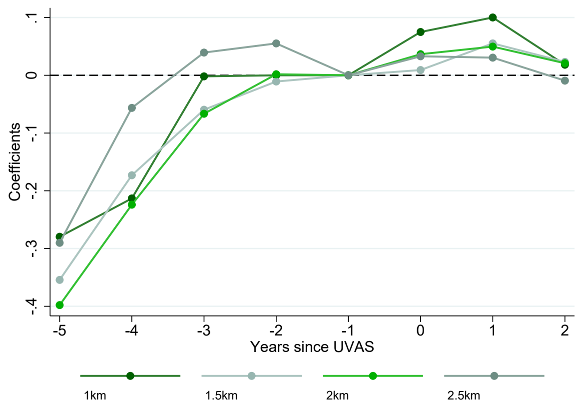


(a) Math (b) Language

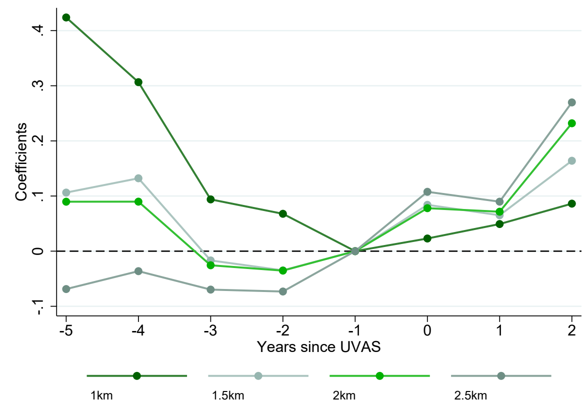
Notes: This figure reports the dynamic coefficients obtained from the estimation of Equation (2). The sample covers the window 5 years before and 2 years after the center opening year. Panel A reports coefficients for the Math test. Panel B reports coefficients for the Language test. Figure reports coefficients for 1, 1.5, 2 and 2,5 buffers around the centers. Far municipalities include Barbosa, Caldas, Girardota, and Sabaneta where there are no units treated regardless of the specification.

Figure D.10: Crime

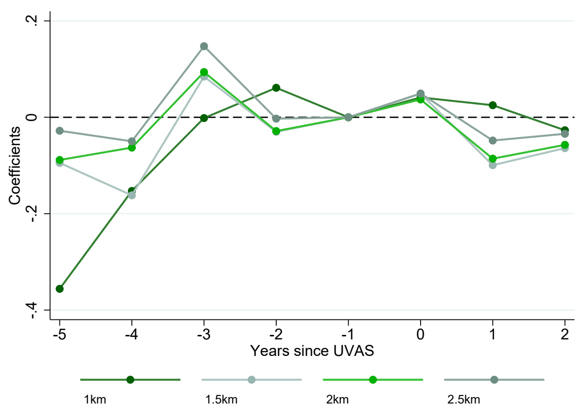
(a) Homicides



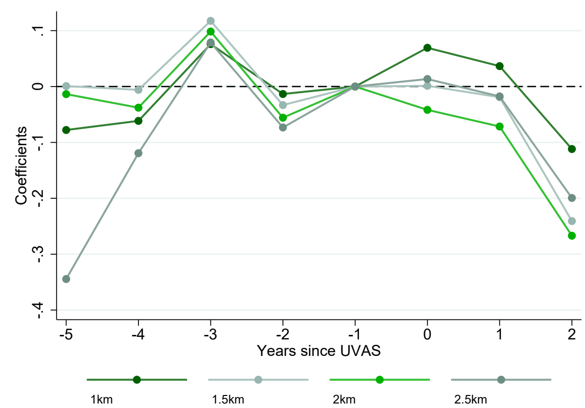
(b) Thefts



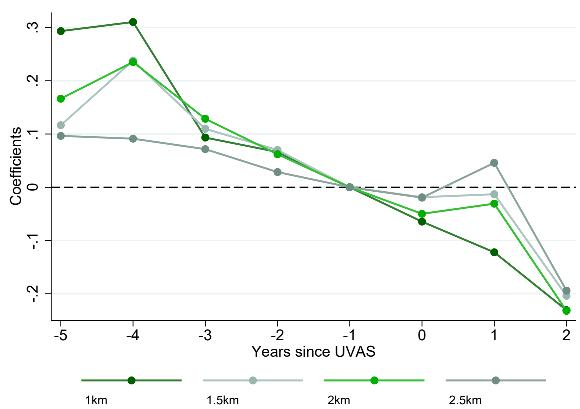
(c) Car thefts



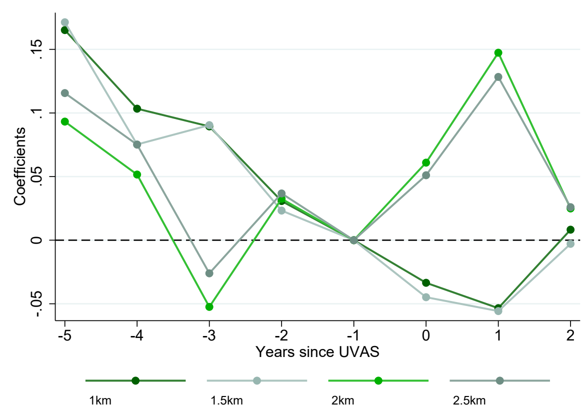
(d) Motorcycle thefts



(e) Residence thefts



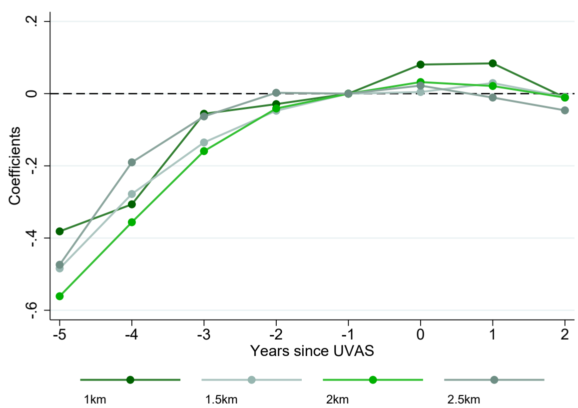
(f) Domestic violence



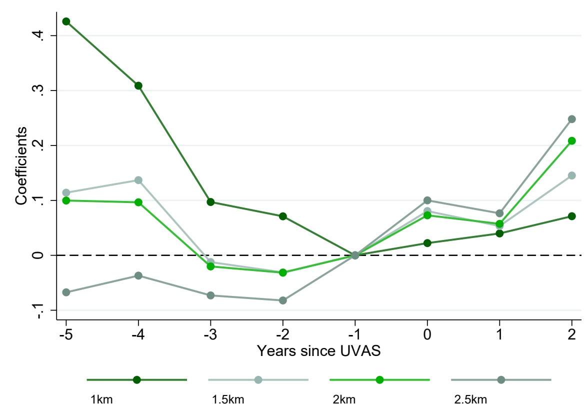
Notes: This figure reports the dynamic coefficients obtained from the estimation of Equation (2). The sample covers the window 5 years before and 2 years after the center opening year. Panels A to F report data on homicides, person, car, motorcycle and residence thefts, and domestic violence. Figure reports coefficients for 1, 1.5, 2 and 2,5 buffers around the centers.

Figure D.11: Crime without distance municipalities

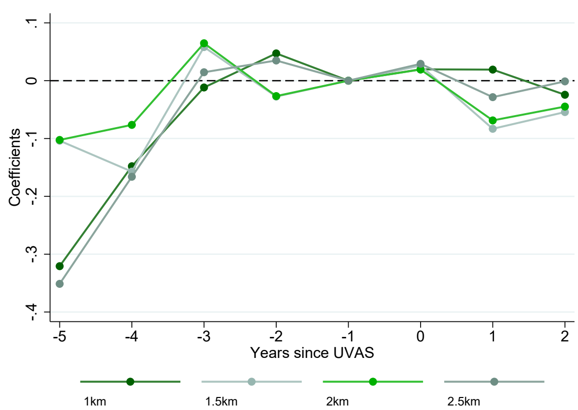
(a) Homicides



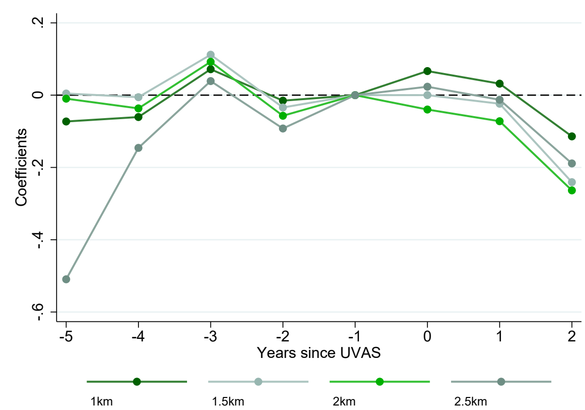
(b) Thefts



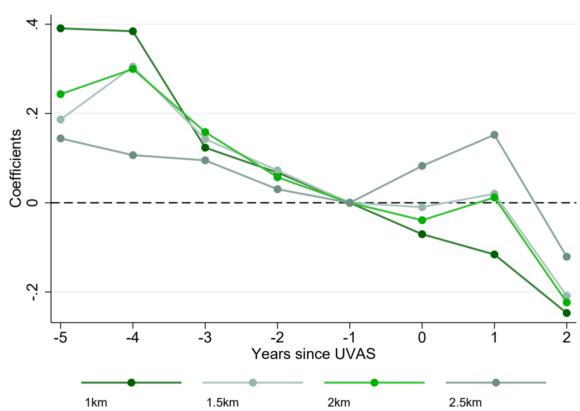
(c) Car thefts



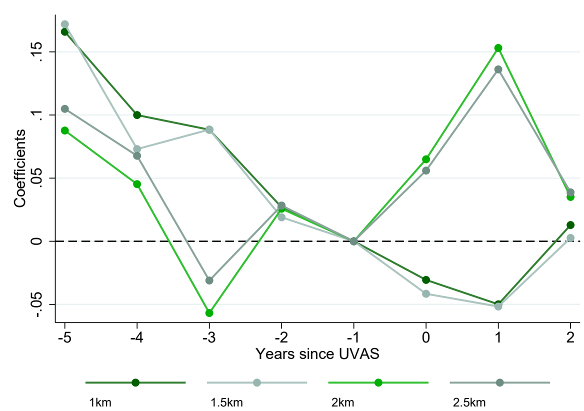
(d) Motorcycle thefts



(e) Residence thefts



(f) Domestic violence



Notes: This figure reports the dynamic coefficients obtained from the estimation of Equation (2). The sample covers the window 5 years before and 2 years after the center opening year. Panels A to F report data on homicides, person, car, motorcycle and residence thefts, and domestic violence. Figure reports coefficients for 1, 1.5, 2 and 2,5 buffers around the centers. Far municipalities include Barbosa, Caldas, Girardota, and Sabaneta where there are no units treated regardless of the specification.

Appendix E Robustness other outcomes

Table E.4: Continuous result other outcomes

	Approved				Dropouts				Transferred			
	Women		Men		Women		Men		Women		Men	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Primary											
Continuos*PostUVA	-0.010	-0.0076	0.0027	0.0064	-0.0018	0.0036	-0.017***	-0.015**	0.020	0.013	0.016	0.0076
	(0.013)	(0.017)	(0.0080)	(0.0084)	(0.014)	(0.020)	(0.0053)	(0.0062)	(0.015)	(0.018)	(0.013)	(0.015)
PostUVA	-0.0094	-0.045	-0.061	-0.14**	0.081	0.073	0.10	0.089	-0.043	-0.025	0.024	0.13
	(0.058)	(0.077)	(0.049)	(0.061)	(0.077)	(0.11)	(0.068)	(0.092)	(0.073)	(0.094)	(0.070)	(0.087)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Avg Non-Standar. Var.	0.90	0.89	0.89	0.88	0.03	0.02	0.03	0.03	0.05	0.06	0.05	0.06
SD Non-Standar. Var.	0.12	0.12	0.14	0.13	0.06	0.05	0.07	0.06	0.09	0.09	0.09	0.08
Schools	1,279	790	1,236	749	1,279	790	1,236	749	1,279	790	1,236	749
Observations	6,566	4,219	6,318	3,978	6,564	4,219	6,316	3,978	6,563	4,219	6,315	3,978
Adjusted R^2	0.40	0.33	0.45	0.36	0.30	0.22	0.35	0.26	0.30	0.22	0.33	0.22
	Secondary											
Continuos*PostUVA	0.015**	0.012	0.016***	0.012**	-0.016**	-0.019**	-0.017***	-0.016**	-0.0079	-0.0025	-0.0078	-0.0056
	(0.0068)	(0.0074)	(0.0053)	(0.0053)	(0.0075)	(0.0087)	(0.0059)	(0.0063)	(0.0078)	(0.0077)	(0.0070)	(0.0077)
PostUVA	0.014	-0.013	-0.032	-0.041	0.030	0.041	0.022	0.029	-0.024	-0.027	0.041	0.042
	(0.049)	(0.057)	(0.043)	(0.051)	(0.048)	(0.063)	(0.049)	(0.068)	(0.054)	(0.057)	(0.045)	(0.052)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Avg Non-Standar. Var.	0.85	0.85	0.82	0.81	0.02	0.02	0.03	0.03	0.06	0.06	0.07	0.07
SD Non-Standar. Var.	0.11	0.11	0.13	0.14	0.04	0.04	0.04	0.05	0.06	0.06	0.06	0.06
Schools	858	538	811	501	858	538	811	501	858	538	811	501
Observations	4,058	2,789	3,784	2,559	4,056	2,788	3,782	2,558	4,058	2,789	3,784	2,559
Adjusted R^2	0.52	0.58	0.62	0.66	0.27	0.27	0.31	0.32	0.34	0.38	0.38	0.44
	Media											
Continuos*PostUVA	0.011	0.0033	0.010	0.0070	-0.0080	-0.0034	-0.0076	-0.0069	-0.0070	-0.00093	-0.0064	-0.0020
	(0.0089)	(0.0086)	(0.0084)	(0.0086)	(0.0078)	(0.0059)	(0.0100)	(0.0097)	(0.0076)	(0.0066)	(0.0088)	(0.0083)
PostUVA	-0.14**	-0.094*	-0.083	-0.048	0.048	0.0028	0.11*	0.081	0.068	0.074	-0.0053	0.0082
	(0.055)	(0.053)	(0.063)	(0.064)	(0.053)	(0.055)	(0.062)	(0.065)	(0.053)	(0.050)	(0.077)	(0.078)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Avg Non-Standar. Var.	0.84	0.84	0.78	0.78	0.02	0.02	0.03	0.03	0.06	0.06	0.07	0.07
SD Non-Standar. Var.	0.13	0.12	0.14	0.14	0.04	0.03	0.04	0.04	0.06	0.06	0.07	0.07
Schools	594	475	551	436	594	475	551	436	594	475	551	436
Observations	3,251	2,779	2,980	2,526	3,251	2,779	2,980	2,526	3,251	2,779	2,980	2,526
Adjusted R^2	0.60	0.62	0.60	0.60	0.37	0.40	0.35	0.35	0.38	0.42	0.32	0.34

Notes: All specifications include school and year fixed effects. Controls are the number of students enrolled, the number of teachers and staff by gender. Robust standard errors are clustered at the school level and are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table E.5: Intensity results other outcomes

	Approved				Dropouts				Transferred			
	Women		Men		Women		Men		Women		Men	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Primary											
1 UVA	0.018	-0.019	-0.012	-0.10	0.073	0.074	0.13	0.10	-0.016	-0.026	-0.025	0.074
	(0.068)	(0.076)	(0.060)	(0.068)	(0.090)	(0.11)	(0.087)	(0.10)	(0.078)	(0.093)	(0.068)	(0.083)
2 UVAs	-0.063	-0.056	-0.098	-0.19**	0.012	-0.050	-0.020	0.034	0.058	0.055	0.14	0.20**
	(0.084)	(0.096)	(0.072)	(0.082)	(0.13)	(0.14)	(0.13)	(0.14)	(0.11)	(0.11)	(0.094)	(0.10)
3 UVAs	0.057	-0.051	0.089	-0.039	0.10	0.052	0.091	0.016	-0.012	0.064	-0.013	0.12
	(0.093)	(0.094)	(0.087)	(0.089)	(0.13)	(0.14)	(0.12)	(0.13)	(0.087)	(0.092)	(0.090)	(0.086)
4 UVAs	-0.22	-0.28	-0.26	-0.46	0.075	0.27	0.51	0.58	0.47	0.38	0.28	0.50
	(0.16)	(0.18)	(0.25)	(0.30)	(0.24)	(0.24)	(0.37)	(0.45)	(0.40)	(0.50)	(0.31)	(0.35)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Avg Non-Standar. Var.	0.90	0.89	0.89	0.88	0.03	0.02	0.03	0.03	0.05	0.06	0.05	0.06
SD Non-Standar. Var.	0.12	0.12	0.14	0.13	0.06	0.05	0.07	0.06	0.09	0.09	0.09	0.08
Schools	1,279	790	1,236	749	1,279	790	1,236	749	1,279	790	1,236	749
Observations	6,566	4,219	6,318	3,978	6,564	4,219	6,316	3,978	6,563	4,219	6,315	3,978
Adjusted R^2	0.40	0.33	0.45	0.36	0.30	0.22	0.35	0.26	0.30	0.22	0.33	0.22
	Secondary											
1 UVA	-0.045	-0.16***	-0.095*	-0.17***	0.087*	0.12*	0.083	0.11	-0.040	0.051	0.076	0.16**
	(0.060)	(0.062)	(0.054)	(0.061)	(0.050)	(0.066)	(0.055)	(0.078)	(0.074)	(0.080)	(0.063)	(0.074)
2 UVAs	-0.029	-0.073	-0.053	-0.043	0.037	0.080	0.092	0.093	-0.0010	-0.010	-0.0034	-0.013
	(0.063)	(0.073)	(0.059)	(0.067)	(0.096)	(0.12)	(0.092)	(0.11)	(0.059)	(0.068)	(0.061)	(0.067)
3 UVAs	-0.072	-0.0058	-0.11	-0.11	0.091	0.017	0.11**	0.084	0.11	0.089	0.076	0.054
	(0.088)	(0.11)	(0.078)	(0.10)	(0.071)	(0.096)	(0.055)	(0.082)	(0.088)	(0.092)	(0.083)	(0.086)
4 UVAs	0.20	-0.39***	0.073	-0.41***	0.17	0.70	0.38	0.71	0.13	0.10	0.16	0.14
	(0.28)	(0.11)	(0.27)	(0.099)	(0.37)	(0.62)	(0.42)	(0.83)	(0.21)	(0.45)	(0.24)	(0.45)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Avg Non-Standar. Var.	0.85	0.85	0.82	0.81	0.02	0.02	0.03	0.03	0.06	0.06	0.07	0.07
SD Non-Standar. Var.	0.11	0.11	0.13	0.14	0.04	0.04	0.04	0.05	0.06	0.06	0.06	0.06
Schools	858	538	811	501	858	538	811	501	858	538	811	501
Observations	4,058	2,789	3,784	2,559	4,056	2,788	3,782	2,558	4,058	2,789	3,784	2,559
Adjusted R^2	0.52	0.58	0.61	0.66	0.27	0.27	0.31	0.32	0.34	0.38	0.38	0.44
	Media											
1 UVA	-0.090	-0.080	-0.069	-0.054	-0.025	-0.036	0.0061	0.0095	0.081	0.096	0.072	0.053
	(0.068)	(0.069)	(0.064)	(0.070)	(0.066)	(0.065)	(0.059)	(0.060)	(0.074)	(0.068)	(0.091)	(0.094)
2 UVAs	-0.13	-0.14	-0.13	-0.16	0.042	0.032	0.26*	0.25	0.076	0.073	0.088	0.13
	(0.092)	(0.11)	(0.097)	(0.11)	(0.089)	(0.10)	(0.14)	(0.17)	(0.081)	(0.089)	(0.081)	(0.089)
3 UVAs	-0.25**	-0.088	-0.28**	-0.17	0.14	0.12	0.014	-0.034	0.064	-0.066	0.11	0.028
	(0.12)	(0.13)	(0.11)	(0.12)	(0.083)	(0.10)	(0.11)	(0.12)	(0.082)	(0.090)	(0.092)	(0.093)
4 UVAs	0.0063	0.13	-0.31	-0.30	0.17	0.16	0.37	0.39	0.18	0.0078	0.079	-0.032
	(0.71)	(0.75)	(0.69)	(0.68)	(0.18)	(0.20)	(0.27)	(0.26)	(0.60)	(0.67)	(0.67)	(0.72)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Avg Non-Standar. Var.	0.84	0.84	0.78	0.78	0.02	0.02	0.03	0.03	0.06	0.06	0.07	0.07
SD Non-Standar. Var.	0.13	0.12	0.14	0.14	0.04	0.03	0.04	0.04	0.06	0.06	0.07	0.07
Schools	594	475	551	436	594	475	551	436	594	475	551	436
Observations	3,251	2,779	2,980	2,526	3,251	2,779	2,980	2,526	3,251	2,779	2,980	2,526
Adjusted R^2	0.60	0.62	0.60	0.60	0.37	0.40	0.35	0.36	0.38	0.42	0.32	0.34

Notes: All specifications include school and year fixed effects. Controls are the number of students enrolled, the number of teachers and staff by gender. Robust standard errors are clustered at the school level and are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.