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The effects of Brazil's basic education reform on juvenile crime.

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Dissertação apresentada ao Programa de Pós-Graduação em Economia da Universidade Federal de Juiz de Fora, como requisito parcial para obtenção do título de Mestre em Economia.

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ABSTRACT

This thesis aims to analyze the relation of education on the juvenile crime committed by 14-year-olds. We use a change in compulsory schooling law passed in Brazil in 2006 that anticipated the entry of youths in the first grade of elementary school. According to the law, new students must be enrolled in this grade at the age of six instead of seven. We argue that a change in the curriculum rather than an extra year of schooling may correlate with crimes. We analyze whether municipalities with a higher proportion of 14-year-olds in this new system reveal changes in criminal outcomes. Although previous literature suggest that this policy has a positive effect on students' academic performance due to improvements in Mathematics and Portuguese scores, which may discourage delinquent behavior, our results indicate a positive correlation between the policy and crime. Estimates show a positive relation between auto thefts committed by 14-year-olds and policy expansion. The results by gender also point to an increase in this crime for both, with greater magnitude for males. Furthermore, our findings evidence that delinquent behavior persists among youths aged 15-17, especially drug dealing. Despite our robustness tests provide additional evidence of the positive relation between crime and the policy expansion, our estimates are still a first investigation that indicates only a correlation between the new policy and criminal outcomes.

Key-words: Education. Compulsory schooling law. Juvenile crime.

RESUMO

Este artigo visa analisar a relação da educação sobre a criminalidade juvenil cometida por jovens de 14 anos de idade. É usada uma mudança na lei de escolaridade compulsória aprovada no Brasil em 2006 que antecipou a entrada de jovens na primeira série do ensino fundamental, com isso a duração do ensino fundamental passou de oito para nove anos. De acordo com a lei, novos alunos devem ser matriculados nesta série aos seis anos de idade ao invés de sete. É argumentado que uma mudança no currículo em vez de um ano extra de escolaridade pode estar correlacionada com os resultados criminais. É analisado se os municípios com maior proporção de jovens de 14 anos neste novo sistema evidenciam variações sobre resultados criminais. Embora resultados anteriores da literatura mostrem que esta política tem um efeito positivo nos resultados acadêmicos dos alunos devido a melhorias nas notas de matemática e português, o que pode desencorajar o comportamento delinquente, os resultados indicam uma correlação positiva entre a política e o crime. As estimativas mostram uma relação positiva entre furtos de carros cometidos por jovens de 14 anos e a expansão da política. Os resultados por gênero também apontam para um aumento deste crime para ambos, com maior magnitude para os homens. Os resultados também evidenciam que o comportamento delinquente persiste entre jovens de 15-17 anos, especialmente no tráfico de drogas. Apesar de os testes de robustez fornecerem evidências adicionais da relação positiva entre o crime e a expansão da política, as estimativas ainda são uma primeira investigação que indicam apenas uma correlação entre a nova política e os resultados criminais.

Palavras-chave: Educação. Lei de escolaridade compulsória. Crime juvenil.

CONTENTS

1 INTRODUCTION

Crime is a problem that affects all countries. Public policies that aim to mitigate the negative consequences of this have a direct impact on reducing homicide rates, incarceration rates and improving the population perception of security.

Other policies may also indirectly affect crime. The literature points to a strong correlation between education and criminal outcomes. Insertion into delinquent behavior depends on the opportunity costs that education provides by increasing individual skills. If the returns of schooling are greater than the returns of crime, the opportunity costs of committing delinquent activity are greater, which discourages individuals from engaging in illicit activity (Lochner, 2007). These costs involve loss of earnings and loss of opportunities in the labor market. On the other hand, if education does not provide higher returns than crime, individuals may be encouraged to commit it because they realize that the opportunity costs of crime may be lower. Education may also influence criminal acts that require more schooling, such as white-collar crime. Therefore, the effects of education on crime can be positive or negative. It depends on the incentives that education may provide.

The returns of education have the greatest impact on the younger population. Criminal behavior in adolescence can generate negative outcomes in adulthood related to declines in earnings, unemployment and the possibility of imprisonment. Young people who commit crime in adolescence may show low academic performance, besides that, they have greater chances of failing or dropping out of school. For this reason, policies aimed at school attendance, educational attainment or keeping them away from crime-stimulating environments play an important role in reducing criminal activities. Youths penalized by justice may again commit crimes due to difficulties of reintegration, social stigma or social exclusion (Hannon, 2003). Beyond the impacts on their own lives, other people are also affected through victimization costs, security expenditures, costs to repair damages, and also from criminal justice system spending (McCollister et al., 2010). Therefore, juvenile crime generates individual and public losses.

Given the importance of education on crime, this thesis examines the relation between juvenile crimes and an educational reform passed in Brazil in 2006. The reform aimed to increase the schooling of basic education students in both public and private schools. In this policy, elementary school years increased from eight to nine years. Prior to the enactment of this law, children were enrolled in the first grade of elementary school at age seven. After that, the mandatory age decreased to six years old. Although this policy has affected all Brazilian states, we only focus on the state of Rio Grande do Sul. The choice of this region was based on the fact that it has fewer restrictions on the crime base and program coverage than other available states.

We explore the difference in treatment intensity across the municipalities of Rio Grande do Sul to find evidence that early entrance reform is related to criminal activities committed by 14 year-olds. We argue that the effect of the reform results from a change in curriculum and not from an additional year of schooling. Individuals exposed to this reform have more time to learn literacy and numeracy, which can help them to understand easier the content taught. These learning gains are reflected throughout basic education, reducing the chances of failing or dropping out of school. This may reflect on better labor market prospects than crime, which may discourage delinquent behavior. Our estimates do not show causality between education and crime due the weakness of our identification assumption. It is only an investigation of the correlation between the new policy and criminal outcomes.

This thesis contributes to the literature that analyzes the effects of education on juvenile crime. Because of its nature, juvenile crime differs from the nature of crimes committed by adults, the effect of education on crime may differ among them. While criminal activities among youths increase during the weekdays and school hours (Taylor-Butts, 2010; Jacob and Lefgren, 2003), crimes committed by adults tend to increase over the weekend. Studies show that adults are prone to commit criminal activities motivated by economic interests and with greater intensity at night. In contrast, financial benefits are not the only factor that determines delinquent behavior among youths. They are also motivated by entertainment, lack of activities in spare time or social status (Goldson and Muncie, 2015; Luallen, 2006). Since educational policies have a larger impact on the younger population, measuring the impact of policy change on this age group captures the effects of the policy more concisely. These effects contribute to keeping youth in school and out of crime-prone environments. Through this, the negative impacts of crime are mitigated, such as youth unemployment, higher crime rates, lower economic growth, and decreases in gross income (Detotto and Otranto, 2010). We also contribute with a new perspective of this policy. Rosa et al. (2019) evaluate the impact of this reform on students' school performance. The results showed that students exposed to the new academic curriculum improved their Mathematics and Portuguese scores. We evaluate the relation between the policy and other social outcomes, that is, juvenile crime.

This thesis is divided as follows. Section 2 focuses on the literature review. Section 3 reviews the institutional background. Section 4 presents the empirical strategy. The main results are in section 5. Finally, section 6 brings a brief conclusion.

2 LITERATURE REVIEW

Education provides a wide range of benefits that extend beyond increases in labor market productivity (Becker and Mulligan, 1997). The effects include health (Lleras-Muney, 2005; Cutler and Lleras-Muney, 2006), citizenship (Oreopoulos and Salvanes, 2011) and crime. They are known as non-production benefits of education (Acemoglu and Angrist, 2000; Lochner, 2011). In the case of crime, education would discourage insertion in criminal activities, which would have short- and long-term effects on crime (Hjalmarsson and Lindquist, 2018). In addition, education produces positive externalities as decreasing incarceration-related expenditures, and tends to contribute to the reduction of deaths (see McCollister et al. (2010) for a crime-costing literature).

Educational attainment may provide long-term effects on criminal activity related to the increase in individual levels of human capital and labor market skills. Higher levels of qualification impact on lower probabilities of unemployment and may increase wage earnings. These factors increase the opportunity costs of crime related to planning and participating in criminal activity (Gould et al., 2002; Machin and Meghir, 2004). Wage changes may have a greater effect on violent (murder, rape, robbery, and assault) crime than on property (burglary, larceny, auto theft, and arson) crime. Although violent crime require less time for planning and execution than property crime, they are associated with higher expected probabilities of arrest, conviction and incarceration (Lochner, 2007).

There are two channels through which education impacts the choice between legitimate work and crime. If marginal returns from investments in education exceed those from crime, then schooling has the power to reduce crime, especially the street one. On the other hand, educational investments can have a positive impact on crime due to the development of criminal skills (Lochner, 2004). For example, white-collar crime (such as forgery, fraud, and embezzlement) can increase with education if they sufficiently reward skills learned in school.

A number of recent studies have empirically estimated a significant negative correlation between educational attainment and crime. In order to allow a causal interpretation, the papers generally use exogenous changes in compulsory schooling laws over time as an instrument for education. In the United States, Lochner and Moretti (2004) estimate the effect of education on participation in criminal activity using changes in state compulsory schooling laws over time. The results showed that an additional year of schooling reduces the probability of incarceration for males and decreases violent and property crimes. In a related work, Bell et al. (2016) analyze the results found in Lochner and Moretti (2004) using the latest database. Estimates showed a negative effect on crime from stricter compulsory schooling laws, but also there is a weaker and sometimes non-existent link between such laws and educational attainment. Using that same exogenous change, similar results are also found in England and Wales (Machin et al., 2011), Italy (Buonanno and Leonida, 2006), Sweden (Hjalmarsson et al., 2015), and in South Africa (Jonck et al., 2015). Cano-Urbina and Lochner (2017) showed for both violent and property crimes a decrease in female arrest rates, whereas there is little impact on white collar crime. In the case of Italian-American mafia, Campaniello et al. (2016) found that white collar crimes increase with education, especially embezzlement and bookmaking.

Other exogenous sources of variation are explored to find a causal effect of educational attainment on crime. Amin et al. (2016) use job training for young adults in United States (e.g., Job Corps) as an instrumental variable for degree attainment. The estimates showed that attainment of a degree also reduces arrest rates. Other studies explore common characteristics of twins to control for unobserved characteristics affecting both criminal behavior and the schooling decisions. Using a sample of Australian twins, Webbink et al. (2012) find that early arrests reduce educational attainment and lower the probability of completing senior high school. In the case of Danish twins, Bennett (2018) estimate that the completion of upper secondary education reduces both violent crime and property crime for males. Despite the use of an alternative exogenous source, these estimates are very close to those found using changes in compulsory schooling laws, reiterating a causal effect of education on crime.

School attendance plays an important role in reducing contemporaneous criminal activities. Firstly, school may have an incapacitating effect (as pointed out by Aizer (2004); Anderson (2014); Fallesen et al. (2018)). Due to the extended school days, the opportunities to commit delinquent behavior are more limited. Students are also less likely to be victims within the school than if they were on the street. However, this effect depends on the ease with which students can engage in crime during the time they are out of school. Extending school days may also provide increases in human capital levels and improve future employment prospects. This raises the imprisonment costs, and discourages engagement in crime while they are enrolled in school. However, it is possible that longer school days may have a positive effect on crime due to the peer effects of crime (see Bayer et al. (2009); Damm and Dustmann (2014); Corno (2017)). Students who are more crime-prone may engage in criminal activities during school as well as encourage other students. Billings and Billings and Phillips (2017) showed that schools with many high risk students may have more negative social interactions, making the school a place that intensifies criminal outcomes.

Empirically, there is a negative correlation between school attendance and crime. The recent studies shed light on the effects by estimating the impacts of different mechanisms that directly affect youth schooling attendance. Beatton et al. (2018) analyse the introduction of an Earning or Learning reform on youth crime in Queensland, Australia. Estimates showed a decrease in property crime as well as impacts on drug crime. In

Sweden, the reform of vocational upper secondary education impacted on decrease in property crimes, although it had no effect on violent crimes, as pointed out by Åslund et al. (2018). Berthelon and Kruger (2011) also found out a decrease in crime rate due to implementation of integral education in Chile.

Other researches, such as Jacob and Lefgren (2003), and Luallen (2006), explore variation in teacher in-service days and teacher strike days, respectively. Both studies find a negative effect on property crimes, but the effect is positive for violent crimes when the school term was interrupted. Fischer and Argyle (2018) explore the adoption of the four-day school week policy across schools in Colorado, in the USA. Their results showed that on average crimes increase as a result of the policy, mainly property crimes. Steinberg et al. (2019) suggest that closing schools characterized by low educational performance may also reduce crime in Philadelphia, mainly violent crime.

School starting age is also explored by literature in order to verify its effects on crime. Children who enter school later tend to be more mature, cognitively developed and engaged in class (Bedard and Dhuey, 2006; Datar, 2006). This positively interferes with learning gains and makes them less likely to fail or drop out of school. As the latter are related to the increase in crime, this policy would contribute to the reduction of youth crime. This policy also affects younger children who interact with older children, and may alter their social interactions or make learning gains through peer interactions within the classroom. Depew and Eren (2016)'s findings suggest that late school entry by one year decreases the incidence of juvenile crime for young black females, particularly in high crime areas. Landersø et al. (2016) and McAdams (2016) also find similar results, with lower propensity to commit crime at younger ages and decreasing incarceration rates, respectively. However, Cook and Kang (2016) pointed out that these individuals are more likely to drop out of high school before graduation and to commit felony offense. This is because some of them reached the minimum age for dropping out of school and did not have sufficient incentives to continue studying. Anderson (2014) showed that increasing the minimum age for dropping out of school impacts on juvenile crime, with positive effects on property crime and arrest rates. However, Anderson et al. (2013)'s findings suggest that it may increase the student victimization due the displacement of crime from the streets to schools.

Despite those previous evidences that support the benefits of delaying school entry, there is still some controversy about this. Elder and Lubotsky (2009) argue that delaying school entry by one year negatively affects children's academic results because they do not accumulate skills earlier, which can generate smaller learning gains. This result is highest among those groups with low educational opportunities. The authors also show that the effect of studying with older colleagues would not generate significant learning gains for younger students. Fuller et al. (2017) support the previous results, showing that children with higher emphasis on academic skills produce better test scores than children with higher emphasis on social skills. Therefore, the interaction among students of different ages is not pointed out as determinant either.

There are important policy lessons regarding education and crime. Interventions focusing on school attendance, educational attainment or keeping youths away from crime-stimulating environments play an important role in reducing delinquent behavior. These policies generate benefits both for them and for society as a whole.

3 INSTITUTIONAL BACKGROUND

The process of the Brazilian basic education reformulation has already been debated in the 1990s. The first regulation was through the Law 9.394 of 1996 that began to allow the enrollment of six-year-old students in a nine-year elementary school system. Through the approval of the National Plan of Education (PNE) in 2001[1] nine-year elementary school became a goal to be achieved for the national education. As of 2006, after the enactment of government Law 11.274 of 2006, the implementation of nine-year elementary school became mandatory. Municipalities should adopt the policy by 2010 in both public schools (municipal, state and federal) and private schools.

Basic education in Brazil is divided into three stages: Preschool, Elementary School, and High School. These stages did not change after the enactment of the law, but there was a change in the time spent in both preschool and elementary school. Figure 1 shows the new organization of Brazilian elementary school before and after the reform. Elementary school increased from eight to nine years and preschool decreased from three to two years. The policy did not affect high school. The main change caused by this law was that instead of students spending three years in preschool (from four years to six years of age), they now remain only two years (until five years old), with the final year of preschool being reversed as the first year of elementary school. As result, students enter elementary school at six years old instead of seven years old. Since preschool was not compulsory[2], the reform can be seen as an increase in one year of schooling for those individuals who probably would not be in school at six years old. According to Ministério da Educação (2009) data, approximately 90% of Brazilian children aged six were already attending school before the policy. Therefore, the effect of one year more of schooling affected only a small percentage of children.

Due to this reform, the total years of basic education are divided as follows. During preschool, students attend two years of school. They are enrolled at four years old and they remain until five years old. Elementary school lasts nine years, with students entering at six years old and finishing at fourteen years old. Finally, after three more years in high school, students complete basic education at seventeen years old[3].

The process to implement the policy was the responsibility of the municipalities. They sent a document to their respective Educational Council (State or Municipal)

[1] Law 10.172 of 2001.

[2] Since the Law 12.796 of 2013, the enrolment of four-year-olds in basic education has been mandatory. Before that, only elementary school was.

[3] For those individuals who do not complete basic education at the stipulated age, the Brazilian educational system offers another option through the Educação para Jovens e Adultos program (EJA). The minimum age to enter this system is eighteen years old in high school and fifteen years old in elementary school. Students attend regular classes and, at the end of the course, take a test that certifies the completion of schooling.

ensuring that their schools were prepared to implement the reform. This included sufficient enrollment for the new students, adequate physical structure and qualified teachers for the new grade.

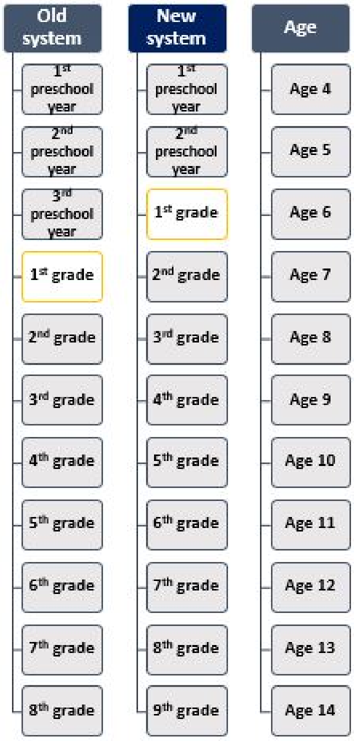

Figure 1 – New organization of Brazilian elementary school before and after the early entrance reform.
Source: Elaborated by the authors.

Another important aspect was the reformulation of the political pedagogical project of schools (PPP). They introduced new contents for first graders and these were different from those taught in the third grade of preschool as well as in the first grade before the reform. Ministério da Educação (2009) argues that the reform cannot be seen merely as an adaptation of school grades, but as an improvement in the quality of education that prioritizes the interests and needs of students. Early entry into elementary school allows students to be literate earlier and to be exposed to content more focused on developing academic skills, unlike in the third grade of preschool, where the focus was on socialization and playing. As a result of that, the new students have more time to learn literacy and numeracy content, which would impact on improving their school performance.

This reformulation of Brazilian basic education only affected new students. If the students were already enrolled in school before the school adopted the policy, they do not suffer from change in the curriculum. They remain in the grade that they were enrolled. In the case where the school adopted the policy before the students were enrolled, they are allocated according to the new system. If the individual is five years old, enrollment must be made in preschool. If the individual completes six years of age the enrollment is made in the first grade of elementary school. Nevertheless, the Brazilian educational system allows schools to accept new student enrollments until a cut-off date. In most Brazilian municipalities, it is until March 31st. In the case of preschool, children can be enrolled if they turn four years old by that date. If the date of birth is after that (e.g. on April 1st), they must expect until the next school year to be enrolled[4]. The same applies for students entering elementary school. If they turn six years old after March 31st, they must remain in preschool until the next school year. Therefore, the cut-off date allows students under the age of six to be in the first grade of elementary school.

As stated, the federal government stipulated that by 2010 all municipalities should adopt the policy. For this reason, it was possible that there would be variations at the time of adoption across regions. This can be explained by the fact that Brazilian education is the responsibility of local governments (states or municipalities) that determine school policies in the region. Depending on their interest, municipalities adopted the reform at different times.

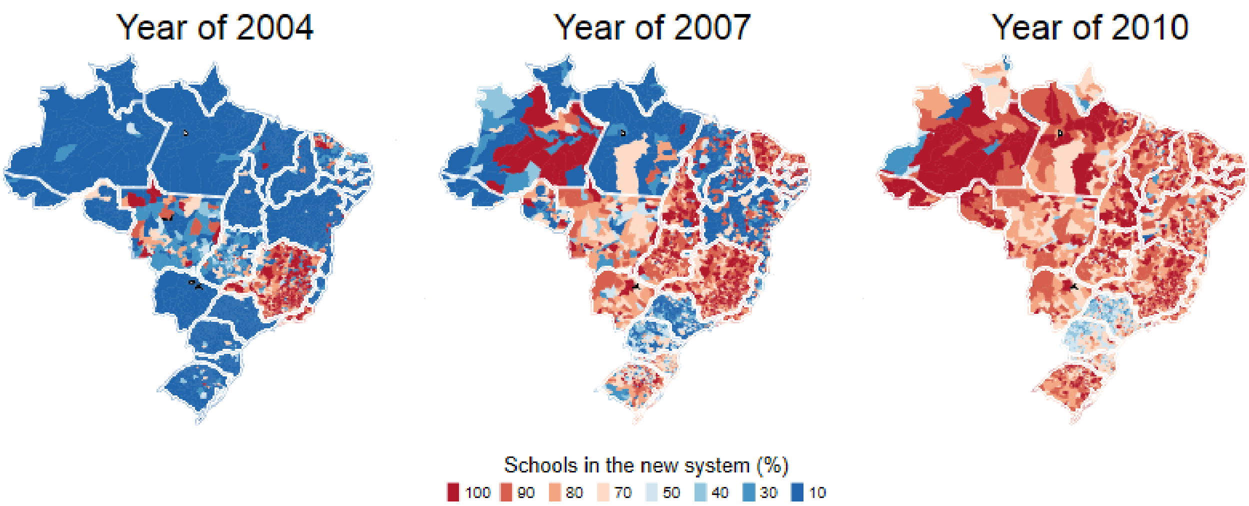

Figure 2 – Early entrance program expansion in Brazil.
Note: This figure shows the proportion of public schools (municipal and state) that adopted the early entrance program by municipality.
Source: School Census, (INEP, 2019). Elaborated by the authors.

In this respect, the state of Rio Grande do Sul presents one of the most gradual coverage of the policy. In some states almost all municipalities had already adopted the reform before the law was enacted. In 2005, the percentage was above 80% of the municipalities in the state of Minas Gerais and 100% in Rio de Janeiro. On the other hand, this percentage in Rio Grande do Sul was only 10.69%. Considering the country,

[4] Normally, the school year starts in February.

27.8% of Brazilian municipalities have adopted the policy in that year. When the law was enacted, both Brazil and Rio Grande do Sul had similar coverage, around 50%. In 2009, coverage reached 99% of municipalities in Rio Grande do Sul and 92% in Brazil.

Schools may also have adopted the regime at different times. Figure 2 shows the proportion of public schools covered by the reform across municipalities and within municipalities. In 2004, the municipalities that are part of the states of Minas Gerais and Rio de Janeiro already had a large proportion of public schools covered by the policy, representing 86.9% and 99.85%, respectively. In the case of Rio Grande do Sul, approximately 5% of public schools implemented the policy in 2004. When the law was enacted, the proportion in the state was close to that of Brazil, with 30.2% and 34.49%, respectively. One year later, the state achieved about 70% coverage while the country was just over 50%.

Therefore, the policy expansion was different among the Brazilian regions. Some of them had already adopted the policy before the enactment of the law and reached the coverage of a large number of municipalities and schools. In the state of Rio Grande do Sul few municipalities had adopted the policy before the law and this process was more gradual.

4 EMPIRICAL STRATEGY

4.1 Summary statistics

We analyze the correlation of the new policy on juvenile crime using an annual panel data from 2004 to 2017. We collect educational information and the number of reported crimes committed by 14 years old youths for each municipality in the state of Rio Grande do Sul.

Although this policy has affected all Brazilian states, we only focus on the state of Rio Grande do Sul. The first reason for choosing this region is the availability of data. We consulted several Departments of Public Security in the Brazilian states and only that of Rio Grande do Sul contained the data we needed. Since we are working with data on offenders, the limitation for obtaining it is even greater, because most official Brazilian data refer to victims. Another limitation was finding data disaggregated by age that had a low number of incomplete information. The data provided by Rio Grande do Sul contain less than 1%. As a comparison, the data provided by the state of São Paulo contain more than 80% of the information without age. The second reason was the coverage of the policy. In the state of Rio de Janeiro, for example, the crime base had a low proportion of incomplete data, but its municipalities already represented a large proportion of coverage even before the law was enacted. On the other hand, the municipalities of Rio Grande do Sul began to implement the policy on a large scale only after the reform. Given these limitations, the choice of this state for the evaluation of this reform is the most appropriate.

Our criminal database contains criminal reports with the address and municipality of occurrence, the type of crime and the date of the fact. The age, date of birth and ethnicity of the offender are also available. Although the address of the crime is available, a small number of this information is complete, not making it feasible to use it in a less aggregate manner than at the municipality level. The names of municipalities are complete in all reported crime information.

We cannot compare municipalities that adopted the reform versus those that did not, because the schools offered the new grade at different times. This could lead to treated and untreated schools being within the same municipality. Given these limitations, we choose to estimate using a treatment intensity variable, which measures the proportion of students covered by the policy in each municipality.

4.1.1 Educational database

We created our educational database using the data available in the School Census. It is an annual survey of statistical data on Brazilian public and private schools. We excluded from the sample private schools, schools located in hamlets, prisons or indigenous areas. Despite the restrictions, our sample corresponds to 80% of the original database.

We calculate our treatment intensity variable using the proportion of students aged 14 years covered by the policy in each municipality. It was created by dividing the total number of 14 year old students enrolled in the new system by the total enrollment of students of this same age. Equation 1 shows how the variable was created for the municipality m in period t. This variable represents the proportion of students covered by the reform.

Equation (1):

$$Prop = \frac{\text{Number of 14-year-olds enrolled in the new system}}{\text{Sum of the number of students aged 14 enrolled in the old and new system}}$$

In the School Census we can obtain the number of students enrolled in the new system per grade and year of birth. The same applies to those enrolled in the old system. Therefore, we are able to separate those who have been treated from those who have not. For example, we have information on the number of individuals who were 14 years old in 2004 (so they were born in 1990) enrolled in the new or old system for each grade. As the expected age to complete elementary school is 14 years, we cannot use the proportion of young people over this age, because we would be selecting individuals who for some reason are not in the appropriate grade. In addition, it is not possible to identify whether students who are in high school, therefore aged 15 or over, have been covered by the policy.

Due to the limitations of the database, we cannot follow the same students over time, we assume that a large proportion of them continue to live in the same locality as six years ago. This is not a huge problem, as we can separate those who have been covered by the program from those who have not been regardless of their region of residence.

Table 1 shows the proportion of students covered by the reform over the years. In the first year of analysis, approximately 7% of them were in the new system at 14 years of age. When the law was enacted, the proportion changed to 10%. It is to be expected that a small proportion of individuals were treated in the first few years after the enactment of the law, as it takes at least eight years for them to reach at least 14 years of age. This is visible in 2014, when the proportion of 14-year-olds reaches 76%.

Table 1 – Descriptive statistics for educational database.

Year	Obs	Mean	Std. Dev.	Min	Max
2004	496	0.07	0.13	0	0.89
2005	496	0.07	0.14	0	0.90
2006	496	0.10	0.17	0	0.92
2007	496	0.10	0.17	0	0.93
2008	496	0.10	0.18	0	0.95
2009	496	0.10	0.17	0	0.90
2010	496	0.12	0.17	0	0.87
2011	496	0.17	0.17	0	0.96
2012	496	0.29	0.17	0	1
2013	496	0.47	0.17	0	0.92
2014	496	0.76	0.15	0	1
2015	496	0.98	0.06	0.15	1
2016	496	0.99	0.03	0.25	1
2017	496	0.99	0.01	0.29	1

Source: School Census, (INEP, 2019). Weighted means for municipal population aged 14 years old.

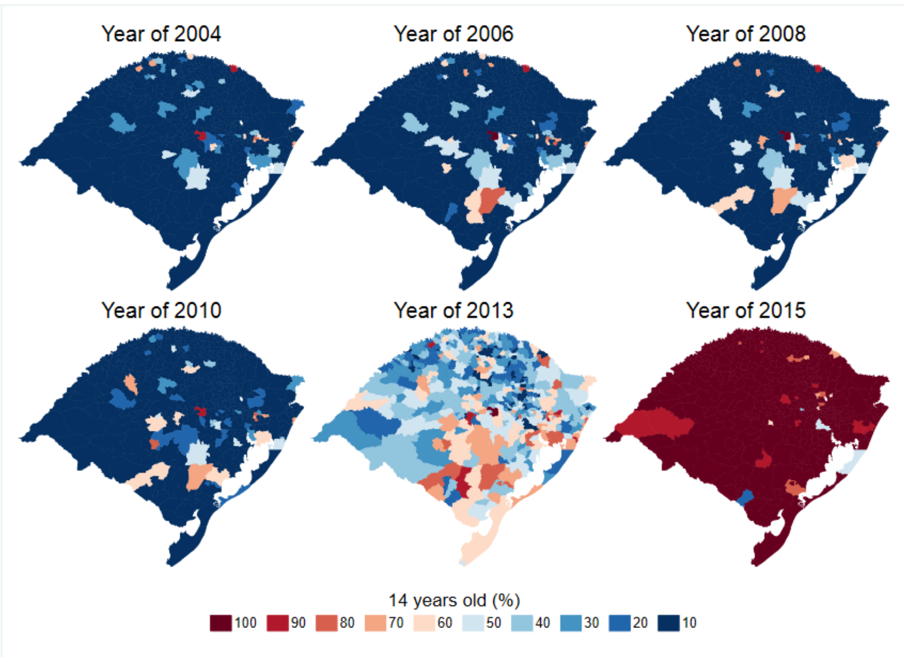

Figure 3 – Early entrance program expansion in the state of Rio Grande do Sul: 14 years old. Note: This figure shows the proportion of public school students aged 14 years old covered by the reform in the municipalities of Rio Grande do Sul. Source: School Census, (INEP, 2019). Elaborated by the authors.

Figures 3 shows the proportion of students aged 14 years old covered by the policy in each municipality of Rio Grande do Sul. We can notice that the variable increases mainly after 2010. This is expected, as individuals affected by the policy at the age of six take a few years to turn 14.

Figure 4 shows the relationship between the treatment intensity variable over time. The proportion of students covered by the policy increases over the years, with some discontinuities in the trend. We expected this pattern because of the age we were using to create our variable.

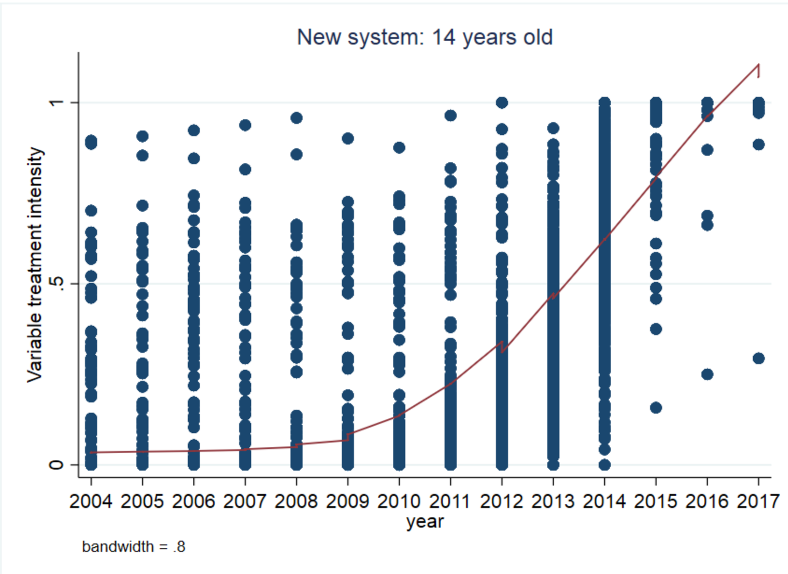

Figure 4 – Lowess smoothing analysis: 14 years old.
Source: Elaborated by the authors.

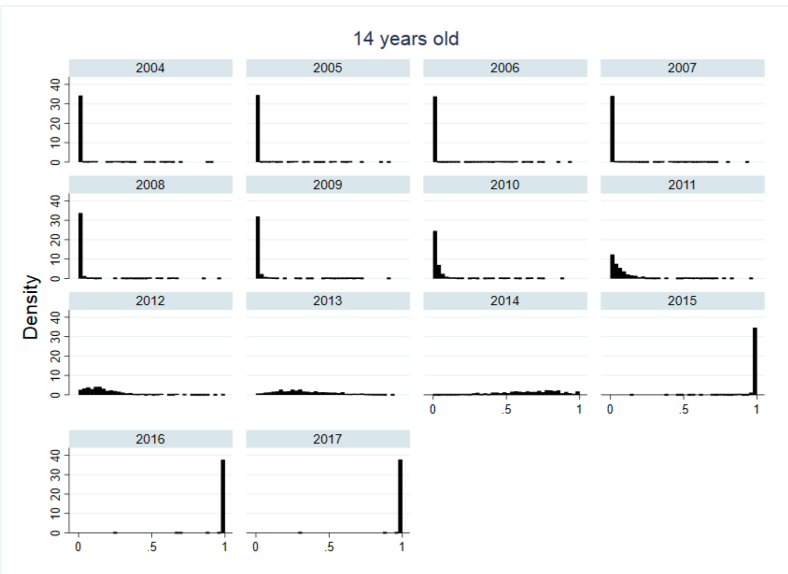

Figure 5 – Histogram analysis: Treatment intensity over the years.
Source: Elaborated by the authors.

Figure 5 represents the histogram analysis of our variable of interest. The density of 14-year-old students begins to shift more visibly in 2010. The complete displacement occurs in 2015.

4.1.2 Crime database

We formulate our crime database using data provided by Department of Public Security of the State of Rio Grande do Sul. Crimes are reported for violent crimes (car theft and murder), auto theft, and drug dealing. Total crime represents the sum of all these crimes.

Crime data are aggregated by the age of the offender at the municipally level. We make an adjustment to this age on the database. Since we have the information on the date of birth of offenders, we use it to calculate their age on the last day of the year in which the report was made. For example, if the crime was committed in April and the offender was born in September, the age used will be that on December 31st. We make this adjustment because on the basis of the School Census, which we use to calculate the proportion of students covered by the reform, the age of the students refers to the last day of the year. We use the log of number of reported crimes committed by 14 year-olds. Equation 2 shows how this variable was created for the municipality m at in period t. We add one unit before the logs are taken.

Equation (2):

$$Crime = Log[(\text{Number of crimes committed by individuals aged 14}) + 1]$$

Table 2 shows the gender, ethnicity and crimes committed for this age. Most of the crimes were committed by men, representing about 84% of the sample. The white population represents the majority of offenders, with 62% aged 14. In relation to these percentage, it should be noted that the population living in the Southern region of Brazil is characterized by a high proportion of white individuals. According to IBGE (2019) data, the white population in Rio Grande do Sul corresponds to 83.22% of total, followed by the brown population with 10.57%. The rest of the sample is composed of non-white people, corresponding to blacks and browns.

On average, the majority of reported crimes are related to drug dealing. This represents an average of 4.07 incidences in the period. Auto theft has the lowest average, at approximately 0.11 incidents for 14-year-olds. When we analyze the average of the sum of the crimes, the incidence corresponds to 4.76.

Table 2 – Descriptive statistics for crime database and controls, 2004-2017.

Variable	Obs	Mean	Std. Dev.	Min	Max
General Characteristics					
Female	6,944	0.16	0.27	0	1
Male	6,944	0.84	0.27	0	1
White	6,944	0.62	0.38	0	1
No white	6,944	0.38	0.38	0	1
Crime					
Total crime	6,944	4.76	13.56	0	90
Auto theft	6,944	0.11	0.40	0	6
Drug dealing	6,944	4.07	12.35	0	82
Car theft	6,944	0.30	0.86	0	6
Murder	6,944	0.26	1.09	0	8
Violent Crime	6,944	0.57	1.73	0	14
Control variables					
Log of GDP per capita	6,944	9.82	0.60	8.15	12.61
Population density	6,944	89.07	325.59	1.57	3146.04
Proportion aged 14	6,944	0.01	0.002	0.00	0.03

Source: Department of Public Security of the State of Rio Grande do Sul; IBGE (2019). Crime variables represent the number of reported crimes. Weighted means are presented.

Since we are using a specific age, many municipalities have zero crime values over the years. We consulted official data from the Department of Public Security of the State of Rio Grande do Sul. These data show the total number of crimes per municipality without considering a specific age. Our database values are very close when we aggregate without considering our specific sample. Although our data include untried crimes, our base may be underestimated. Considering that not all crimes are reported, it is possible that a greater number of crimes occurred compared to those that were recorded. Our number of observations is also limited because we excluded the reports as victims, which represents the vast majority of observations (80%). Although there are these restrictions, we consider that the observations reflect the criminal behavior of these youths, because it includes all available reported crimes. We understand that a high number of information equal to zero may influence the results, but since the number of crimes in our base is very close to that observed in official reports and that we have a low amount of incomplete data, we believe that the values actually reflect the behavior of this age in the state.

4.1.3 Methodology

This study aims to analyze the relation of early entrance reform on reported crimes committed by 14 year olds. We investigate whether individuals exposed to treatment in the first grade of elementary school are less likely to commit crimes in adolescence. We calculated for each year of analysis the proportion of individuals in each municipality aged 14 who were covered by the program. We argue that these individuals were exposed to the new system when they were 6 years old. As stated earlier, we can separate treated and untreated individuals. When the school adopts the policy, the enrollment of new students is computed in a School Census variable that differs from the old system. Therefore, if students were treated at age 6, their enrollment at age 14 is in this variable, which indicates that they are in the new system. The enrollment of students not exposed to the policy remains in the variable of the old system.

The starting point of our analysis is that the effect of the reform results from a change in the curriculum and not from an additional year of schooling. As stated, the policy has made new students increase their academic skills instead of just focusing on socialization and playing. Individuals exposed to this reform have more time to learn literacy and numeracy, which can help them to understand the content taught more easily. These learning gains are reflected throughout basic education, reducing the chances of failing or dropping out of school. It can discourage them from committing crimes during adolescence due to the opportunities in the labor market may be greater than those of crime. Rosa et al. (2019) also use the same argument to estimate the effect of this policy on student's performance. They find that students exposed to this change in the curriculum improve their Mathematics and Portuguese scores. Qualitative studies support this change in curriculum through interviews with teachers and document analysis, such as Jacomini et al. (2012) and Pansini and Marin (2011).

Our empirical strategy to estimate the relation of early entrance reform on juvenile crime is based on the construction of a treatment intensity variable. This variable represents the proportion of students covered by the policy in relation to the total number of students in each municipality. We can use this approach because our variable is continuous and varies across municipalities.

Our crime variables are the log of number of reported crimes committed by 14 years old youths for each municipality. Our main assumption is that the variation in the proportion of students covered by the program is unlikely to be correlated with reported crimes. There is no evidence that the reform was implemented to reduce crime in any region, especially in the peripheries. If a municipality underreports crimes, either as a whole or for a specific age group, such as the group we are using, to justify the benefits of this reform, this would be a problem.

We estimate the following regression:

Equation (3):

$$Crime_{amt} = \alpha + \beta_1 Prop_{amt} + \beta_2 M_m + \beta_3 T_t + \beta_4 X_{mt} + \epsilon_{mt}$$

where a represents individuals aged 14, m municipality, and t represents the time.

In equation (3), the dependent variable *Crime* denotes the log of number of reported crimes committed in municipality m at time t. *Prop* is the treatment intensity variable in the municipality m at time t. The variable M represents municipality fixed effects and control for differences in municipalities that are common across years. The variable T indicates year fixed effects and control for differences across time that are common to all municipalities. We also include control variables represented by vector X. We control for population density, proportion of youths aged 14 years old, and the log of GDP per capita. We deflated it by the implicit deflator of Gross Domestic Product (GDP) with the base year 2010. The population density variable corresponds to the total number of inhabitants in the municipality divided by its total area.

Our coefficient of interest is β_1 and it corresponds to the estimative of the relation between the proportion of students covered by the policy and the crime variable. This estimate measures whether municipalities with higher proportion of students treated experienced a greater decrease in reported crime rate.

We estimate our model using weighted least squares. The weight used is the municipal population aged 14 years old. The standard errors estimated are clustered at the municipal level. This procedure accounts for the potential serial correlation of error terms over time within a municipality (Bertrand et al., 2004).

5 RESULTS

5.1 Juvenile crime and the early entrance reform

Table 3 shows the main results of our coefficient β_1 of equation (3) for each type of crime. Each column represents a separate regression. Columns 1-6 represent the estimates using weighted least squares. Appendices 14-19 contain the most detailed estimates for each type of crime.

The Prop variable measures how the increase of one percentage point in the proportion of enrollments in the new system affects the number of crimes. The findings indicate that the exposure to reform increases auto thefts committed by 14-year-olds. An one percentage point increase in the proportion of treated students affects by 0.21% the number of auto thefts. Total crime, drug dealing, murder, car theft and violent crime were not significant. This indicates that a one percentage point increase in the treatment intensity variable does not significantly affect these crimes.

Table 3 – Juvenile crime and the early entrance reform, 2004-2017.

Variables	(1) Total crime	(2) Auto theft	(3) Drug dealing	(4) Murder	(5) Car theft	(6) Violent crime
Prop	0.10	0.21**	0.08	-0.31	-0.10	-0.23
	(0.20)	(0.09)	(0.21)	(0.24)	(0.10)	(0.20)
Population density	0.00*	-0.00*	0.00	0.00	0.00**	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GDP per capita	-0.15	0.07	-0.21	-0.05	0.03	-0.01
	(0.20)	(0.05)	(0.18)	(0.09)	(0.06)	(0.08)
Proportion aged 14	11.34	0.43	14.18	3.41	-1.65	0.30
	(9.39)	(2.03)	(9.07)	(4.80)	(2.74)	(3.87)
Constant	0.23	-0.21	0.82	-1.91	-1.05	-1.84
	(1.89)	(0.44)	(1.87)	(1.67)	(0.93)	(1.65)
Observations	6,944	6,944	6,944	6,944	6,944	6,944
R-squared	0.26	0.08	0.29	0.29	0.11	0.21
Number of municipalities	496	496	496	496	496	496

Each column represents a separate regression. Our dependent variables are the log of the number of total crime, auto theft, drug dealing, murder, car theft and violent crime. We control for population density, log of GDP per capita, and proportion of youths aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 14 years old. *** p<0.01, ** p<0.05, * p<0.1.

Our estimates remain significant and positive even with the addition of control variables. The magnitude is also very close as we use them. The same is true for those crimes that were not significant. They remain without significance even after the use of controls (see Appendices 14-19 for more details).

Although we expect a negative correlation on crime, this policy can also have a positive correlation on that. Individuals more likely to commit crimes are also affected by it. They can commit delinquencies within school or encourage other peers to commit crimes. The effects may include the increase in cases of gang activity or decrease in the perception of school safety. This delinquent behavior can also happen outside of school, increasing the number of crimes committed around it. Some studies support this argument. Billings and Phillips (2017) showed that schools with many high risk students may have more negative social interactions, making the school a place that intensifies criminal outcomes. Bayer et al. (2009), Damm and Dustmann (2014), and Corno (2017) show the peer effects of crime. Students who are more crime-prone may engage in criminal activities during school as well as encourage other students. Although we cannot identify which students are more likely to commit crimes and whether they may be interfering with the positive outcomes we find, the above evidence indicates a likely mechanism in which the policy correlates with crime.

We also estimate the relation of reform by gender. However, we could not calculate the proportion of individuals treated by it before 2007 due to the School Census which does not allow us to separate the number of enrollments per year of birth between these groups. Although our estimates begin in 2007, we do not believe that this is a problem, since the higher proportion of enrollments increases after 2010.

Table 4 shows the results for males. Tables 20-25 contain the most detailed results. We also found an increase in the crime for them. A one percentage point increase in the proportion of men covered by the reform affects by 0.20% the number auto thefts. The magnitude is very close when we do not estimate for males and females separately. Moreover, even with the use of a panel containing a shorter period of time, the estimate remains significant and positive for auto theft. The other types of crime are still not significant, suggesting that the reform for males has no relation on these categories.

Table 4 – Males: juvenile crime and the early entrance reform, 2007-2017.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Total crime	Auto theft	Drug dealing	Murder	Car theft	Violent crime
Prop	0.23	0.20**	0.19	-0.33	-0.09	-0.21
	(0.27)	(0.08)	(0.29)	(0.23)	(0.11)	(0.18)
Population density	0.00	-0.00**	0.00	0.00	0.00**	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GDP per capita	-0.32	0.01	-0.29	-0.08	-0.09	-0.15
	(0.22)	(0.05)	(0.19)	(0.12)	(0.08)	(0.14)
Proportion aged 14	21.99	-3.90	22.67	6.97	-0.33	5.82
	(16.87)	(4.43)	(15.17)	(8.43)	(5.23)	(7.89)
Constant	3.07	0.35	2.90	-1.65	0.42	-0.09
	(2.32)	(0.53)	(2.00)	(1.98)	(0.84)	(1.58)
Observations	5,456	5,456	5,456	5,456	5,456	5,456
R-squared	0.18	0.08	0.18	0.29	0.10	0.21
Number of municipalities	496	496	496	496	496	496

Each column represents a separate regression. Our dependent variables are the log of the number of total crime, auto theft, drug dealing, murder, car theft and violent crime committed by males. We control for population density, log of GDP per capita, and proportion of males aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old males. *** p<0.01, ** p<0.05, * p<0.1.

For females, the results in Table 5 also show an increase in the incidence of auto theft. The correlation is estimated to be a 0.06% increase in the number of this crime committed by them. The results remain similar even with the addition of the control variables. See Appendices 26-31 for more details.

Although our sample is composed mostly of males, our results are a good suggestion for the delinquent behavior of females in this policy. Cano-Urbina and Lochner (2017) found out that increases in average state schooling levels reduce female arrest rates for violent and property crime but has less effect on white-collar crimes. Our estimates show a positive result among one type of property crime - auto theft. However, we are not evaluating the additional year of schooling as Cano-Urbina and Lochner (2017), but rather a change in the student's curriculum. This may be an indication that our policy is not sufficient to discourage delinquent behavior among females. We have no information on white-collar crimes to estimate whether the change in the curriculum also affects this type of crime.

Table 5 – Females: juvenile crime and the early entrance reform, 2007-2017.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Total crime	Auto theft	Drug dealing	Murder	Car theft	Violent crime
Prop	0.01	0.06**	0.05	-0.14	-0.03	-0.16
	(0.07)	(0.03)	(0.10)	(0.10)	(0.02)	(0.10)
Population density	0.00***	-0.00	0.00*	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GDP per capita	0.00	0.02	0.03	0.01	-0.04	-0.03
	(0.15)	(0.01)	(0.11)	(0.02)	(0.06)	(0.05)
Proportion aged 14	6.45	3.47	5.72	-0.47	-0.68	-1.15
	(8.19)	(2.17)	(7.56)	(1.36)	(1.76)	(2.34)
Constant	-0.54	-0.07	-0.62	-0.62	0.43	-0.19
	(1.66)	(0.12)	(1.20)	(0.50)	(0.61)	(0.68)
Observations	5,456	5,456	5,456	5,456	5,456	5,456
R-squared	0.06	0.13	0.06	0.19	0.03	0.13
Number of municipalities	496	496	496	496	496	496

Each column represents a separate regression. Our dependent variables are the log of the number of total crime, auto theft, drug dealing, murder, car theft and violent crime committed by females. We control for population density, log of GDP per capita, and proportion of females aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old females. *** p<0.01, ** p<0.05, * p<0.1.

To check whether the estimates are persistent at other ages, we calculate the correlation of the policy for young people aged 13-17, separately. To calculate the proportion of 13-year-olds covered by the reform, we use the same approach as for 14-year-olds. In the case of other ages, we use the values with lag. For example, to calculate the proportion of 15-year-olds in 2006, we used the proportion of 14-year-olds in 2005. As we mentioned, we could not separate which students were covered by the policy after that age. Even with this limitation, the variables are able to capture the proportion of students covered at 15, 16, and 17 years of age. We did not use 18-year-olds because the expected age for completion of high school is 17 and other factors can interfere with delinquent behavior.

As expected, the relation at these ages is also positive on crime. Crimes committed by 13-year-olds (see Table 6) include auto thefts and car thefts. In the case of the former, the relation persists at other ages and its magnitude also increases. It changes from 0.05% at age 13 to 0.21% at age 14. For 15-year-olds, the relation is even greater, estimated at 0.27%. At subsequent ages it is not significant.

Table 6 – 13 years old: juvenile crime and the early entrance reform, 2004-2017.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Total crime	Auto theft	Drug dealing	Murder	Car theft	Violent crime
Prop	0.04	0.05**	-0.04	-0.12	0.11**	-0.01
	(0.15)	(0.02)	(0.15)	(0.09)	(0.06)	(0.06)
Population density	0.00	0.00	0.00*	0.00	-0.00**	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GDP per capita	0.06	0.06	-0.01	-0.01	0.03	0.01
	(0.10)	(0.04)	(0.11)	(0.04)	(0.02)	(0.03)
Proportion aged 13	9.32*	0.24	8.63	4.30**	-0.77	3.53**
	(5.63)	(1.22)	(5.28)	(2.00)	(0.84)	(1.63)
Constant	-1.44*	-0.64	-0.93	-0.70	0.25	-0.45
	(0.86)	(0.44)	(0.88)	(0.63)	(0.21)	(0.52)
Observations	6,944	6,944	6,944	6,944	6,944	6,944
R-squared	0.20	0.03	0.20	0.17	0.11	0.11
Number of municipalities	496	496	496	496	496	496

Each column represents a separate regression. Our dependent variables are the log of the number of total crime, auto theft, drug dealing, murder, car theft and violent crime. We control for population density, log of GDP per capita, and proportion of youths aged 13 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 13 years old. *** p<0.01, ** p<0.05, * p<0.1.

Table 7 – 15 years old: juvenile crime and the early entrance reform, 2005-2017.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Total crime	Auto theft	Drug dealing	Murder	Car theft	Violent crime
Prop	0.14	0.27***	-0.00	-0.25	-0.01	-0.01
	(0.19)	(0.10)	(0.21)	(0.28)	(0.18)	(0.22)
Population density	0.00	-0.00	0.00	0.01	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GDP per capita	-0.38**	0.02	-0.34**	-0.40***	-0.25	-0.48**
	(0.16)	(0.05)	(0.17)	(0.13)	(0.16)	(0.21)
Proportion aged 15	85.16**	-35.63**	77.72**	121.43**	77.46***	115.13***
	(37.23)	(16.42)	(36.52)	(56.43)	(29.34)	(34.78)
Constant	1.57	1.06	1.60	-1.90	-0.88	-0.05
	(1.86)	(1.12)	(1.80)	(2.81)	(1.55)	(2.06)
Observations	6,448	6,448	6,448	6,448	6,448	6,448
R-squared	0.35	0.06	0.34	0.39	0.22	0.34
Number of municipalities	496	496	496	496	496	496

Each column represents a separate regression. Our dependent variables are the log of the number of total crime, auto theft, drug dealing, murder, car theft and violent crime. We control for population density, log of GDP per capita, and proportion of youths aged 15 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 15 years old. *** p<0.01, ** p<0.05, * p<0.1.

Another important aspect is that the type of crime changes for 16-17 year olds. Drug dealing and total crime represent an increase at these ages. Estimates in Table 8 shows that a one percentage point increase in the proportion of 16 year olds treated represents an increase of 0.31% and 0.38% in the number of drug dealing and total crime, respectively. The relation is even greater for 17-year-olds. Estimates in Table 9 show that there is an increase of 0.47% in the case of drug dealing and 0.42% in total crime. The relation between the other crimes and the policy remain not significant for these ages even using control variables.

Table 8 – 16 years old: juvenile crime and the early entrance reform, 2006-2017.

Variables	(1) Total crime	(2) Auto theft	(3) Drug dealing	(4) Murder	(5) Car theft	(6) Violent crime
Prop	0.38**	0.08	0.31*	-0.25	0.27	0.21
	(0.17)	(0.10)	(0.19)	(0.35)	(0.16)	(0.24)
Population density	0.00	0.00	0.00	0.01*	0.00***	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GDP per capita	-0.05	0.04	-0.12	-0.33*	0.06	-0.16
	(0.15)	(0.07)	(0.16)	(0.18)	(0.15)	(0.18)
Proportion aged 16	54.74	7.18	59.90	206.95*	70.86**	120.48**
	(37.92)	(17.84)	(47.17)	(108.83)	(34.09)	(57.62)
Constant	-0.52	-0.61	0.11	-5.52	-3.67**	-3.38
	(2.05)	(0.82)	(2.24)	(4.35)	(1.77)	(2.68)
Observations	5,952	5,952	5,952	5,952	5,952	5,952
R-squared	0.38	0.06	0.35	0.43	0.20	0.37
Number of municipalities	496	496	496	496	496	496

Each column represents a separate regression. Our dependent variables are the log of the number of total crime, auto theft, drug dealing, murder, car theft and violent crime. We control for population density, log of GDP per capita, and proportion of youths aged 16 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 16 years old. *** p<0.01, ** p<0.05, * p<0.1.

Table 9 – 17 years old: juvenile crime and the early entrance reform, 2007-2017.

Variables	(1) Total crime	(2) Auto theft	(3) Drug dealing	(4) Murder	(5) Car theft	(6) Violent crime
Prop	0.42**	-0.16	0.47***	0.06	0.25	0.35
	(0.17)	(0.11)	(0.18)	(0.28)	(0.21)	(0.25)
Population density	0.00	-0.00**	-0.00	0.01*	0.00**	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GDP per capita	-0.30**	-0.06	-0.27*	-0.42**	-0.36**	-0.55***
	(0.13)	(0.12)	(0.14)	(0.17)	(0.16)	(0.18)
Proportion aged 17	-5.69	-91.40**	-44.12	275.19*	210.28***	236.14***
	(56.28)	(40.81)	(84.15)	(141.60)	(74.85)	(79.48)
Constant	4.04**	3.42***	4.22	-6.24	-2.00	-1.14
	(1.75)	(1.23)	(2.64)	(5.49)	(2.51)	(3.07)
Observations	5,456	5,456	5,456	5,456	5,456	5,456
R-squared	0.39	0.04	0.37	0.48	0.19	0.41
Number of municipalities	496	496	496	496	496	496

Each column represents a separate regression. Our dependent variables are the log of the number of total crime, auto theft, drug dealing, murder, car theft and violent crime. We control for population density, log of GDP per capita, and proportion of youths aged 17 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 17 years old. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The above estimates provide some indications of the criminal behavior of youths. First, we notice that the magnitude of the results increases with age, especially auto thefts. Other crimes remain insignificant among 13-15 year olds, excluding car theft for 13 years old. For young people aged 16-17, involvement in delinquent behaviour is related to drug dealing. The magnitude is even greater for those who are 17 years old. In both ages total crime is also significant. Therefore, we observe a change in delinquent behavior as age increases.

Our estimates converge to the statements of Farrington (1986); Piquero et al. (2007) and Bosick (2009). They argue that criminal behavior among young people grows between 15 and 19 years old. Among those ages, youths are more likely to commit delinquent behavior. Our estimates may be capturing this relation due to the increase in the magnitude of the estimates as the age increases.

It is important to highlight some caveats on our empirical strategy. First, our analysis has high internal validity, but low external validity. Brazil is a country that presents great cultural and population diversity, restricting our ability to generalize our estimates to other regions, especially when our results refer mainly to reports of crimes committed by white people, which in other regions, such as the North and Northeast, do not represent the majority of the population.

Another limitation is the restriction of the database. Our analysis is based on a specific age group and for offenders. This greatly limits the number of observations with values other than zero. However, as we argued, we have strong evidence that our base reflects the criminal behavior of them.

Finally, we understand that estimates for total crime and drug dealing may be more robust due to the higher number of cases. Since we have less information for auto thefts and car thefts, the estimates may be more sensitive to some variations that occur in the number of such crimes in municipalities.

5.2 Robustness check

In order to evaluate the robustness of our results, we estimate the correlation of the policy using other specifications. We created the log of crime reports per 100,000 of the 14 years old population. We calculate the number of inhabitants of this age using the Instituto Brasileiro de Geografia e Estatística data (IBGE, 2019; Sidra, 2019).

The equation 4 shows how the variable is created.

Equation (4)

$$Crime = Log[(\frac{\text{Number of crimes committed by individuals aged 14}}{\text{Number of inhabitants of age 14 in the municipality}})x100,000]$$

Table 10 shows that results for 14-year-olds remain significant and positive. Estimates indicate that an one-percentage point increase in program coverage affects the incidences by 2.94% of auto theft rate. The other crimes are still not significant, even when we use this new variable. Tables 32-37 show that the magnitude of the relation remains consistent even with the addition of control variables.

The same pattern is found when we estimate by gender. For females, an one-percentage point increase in program coverage affects the incidences by 1.01% of auto theft rate. For males it is even greater, with an increase by 2.96%. See Table 11 and 12 for more details.

Table 10 – Estimates for the log of crime rate, 2004-2017.

Variables	(1) Total crime	(2) Auto theft	(3) Drug dealing	(4) Murder	(5) Car theft	(6) Violent crime
Prop	0.75	2.94**	1.19	-1.70	-0.19	0.56
	(1.32)	(1.19)	(1.37)	(1.58)	(1.11)	(1.04)
Populational density	0.00	-0.01*	0.00	0.02	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
GDP per capita	0.58	1.02	-0.70	-0.74	0.55	0.27
	(1.13)	(0.66)	(1.51)	(1.00)	(0.87)	(1.23)
Proportion aged 14	-23.12	-70.08**	24.99	-23.75	-83.73**	-59.09
	(66.07)	(30.38)	(66.70)	(54.43)	(36.06)	(42.28)
Constant	-9.08	-7.05	0.94	-14.37	-18.38	-13.03
	(11.09)	(5.40)	(15.96)	(12.16)	(11.93)	(13.37)
Observations	6,944	6,944	6,944	6,944	6,944	6,944
R-squared	0.14	0.08	0.20	0.23	0.08	0.11
Number of municipalities	496	496	496	496	496	496

Each column represents a separate regression. Our dependent variables are the log of total crime rate, auto theft rate, drug dealing rate, murder rate, car theft rate and violent crime rate. We control for population density, log of GDP per capita, and proportion of youths aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 14 years old. *** p<0.01, ** p<0.05, * p<0.1.

Table 11 – Females: estimates for the log of crime rate, 2007-2017.

Variables	(1) Total crime	(2) Auto theft	(3) Drug dealing	(4) Murder	(5) Car theft	(6) Violent crime
Prop	0.80	1.01**	0.64	-2.21	-0.33	-2.58
	(1.04)	(0.46)	(1.21)	(1.69)	(0.26)	(1.67)
Populational density	0.01	-0.00	0.01	0.01	-0.00	0.01
	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
GDP per capita	0.17	0.38*	0.72	0.30	-0.58	-0.40
	(2.38)	(0.19)	(1.55)	(0.34)	(0.95)	(0.82)
Proportion aged 14	-83.72	-111.45***	-99.27	-177.00***	-172.42***	-180.28***
	(138.32)	(37.64)	(128.76)	(25.50)	(25.15)	(36.41)
Constant	-11.19	-7.04***	-16.94	-16.22*	1.73	-8.60
	(25.91)	(1.89)	(17.57)	(8.36)	(9.79)	(11.10)
Observations	5,456	5,456	5,456	5,456	5,456	5,456
R-squared	0.04	0.13	0.05	0.19	0.05	0.14
Number of municipalities	496	496	496	496	496	496

Each column represents a separate regression. Our dependent variables are the log of total crime rate, auto theft rate, drug dealing rate, murder rate, car theft rate and violent crime rate committed by females. We control for population density, log of GDP per capita, and proportion of females aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 year old females. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 12 – Males: estimates for the log of crime rate, 2007-2017.

Variables	(1) Total crime	(2) Auto theft	(3) Drug dealing	(4) Murder	(5) Car theft	(6) Violent crime
Prop	1.54	2.96***	1.59	-1.87	0.00	0.83
	(1.44)	(1.08)	(1.45)	(1.57)	(1.24)	(0.91)
Populational density	-0.01	-0.01**	-0.01	0.02*	0.01	0.00
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
GDP per capita	-0.01	0.22	-0.56	-1.26	-1.20	-1.76
	(1.00)	(0.73)	(1.03)	(1.55)	(1.10)	(1.59)
Proportion aged 14	-87.40	-244.89***	-31.32	-87.96	-190.63***	-108.77
	(118.56)	(62.33)	(114.33)	(91.61)	(64.64)	(86.20)
Constant	3.09	0.99	7.20	-7.90	2.84	11.48
	(12.97)	(8.42)	(13.84)	(18.07)	(11.54)	(17.81)
Observations	5,456	5,456	5,456	5,456	5,456	5,456
R-squared	0.10	0.10	0.10	0.22	0.07	0.10
Number of municipalities	496	496	496	496	496	496

Each column represents a separate regression. Our dependent variables are the log of total crime rate, auto theft rate, drug dealing rate, murder rate, car theft rate and violent crime rate committed by males. We control for population density, log of GDP per capita, and proportion of males aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 year old males. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

We also check if our results remain consistent when the estimates contain private schools. We calculate our treatment intensity variable with the sum of public and private school enrollments in each municipality. Therefore, this proportion refers to the sum of these two models of education, which is different from our variable used in the preferred model that takes only public schools into account. Table 13 indicates that the magnitude is positive and similar in this case. The other crimes are still not significant in this estimation. We have not analyzed the relation of the policy with private schools because unobserved characteristics can interfere with a child's enrolment in a private school. Perception of better quality education, more learning and opportunities in the labor market may be affecting this choice.

Table 13 – Estimates for students in public and private schools, 2004-2017.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Total crime	Auto theft	Drug dealing	Murder	Car theft	Violent crime
Prop	-0.03	0.22**	-0.08	-0.33	-0.07	-0.22
	(0.23)	(0.10)	(0.24)	(0.26)	(0.09)	(0.20)
Populational density	0.00*	-0.00*	0.00	0.00	0.00**	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GDP per capita	-0.16	0.07	-0.22	-0.05	0.03	-0.00
	(0.20)	(0.05)	(0.19)	(0.09)	(0.06)	(0.08)
Proportion aged 14	11.32	0.42	14.16	3.43	-1.64	0.31
	(9.32)	(2.04)	(9.03)	(4.82)	(2.75)	(3.86)
Constant	0.31	-0.19	0.91	-1.93	-1.07	-1.86
	(1.90)	(0.45)	(1.89)	(1.68)	(0.95)	(1.67)
Observations	6,944	6,944	6,944	6,944	6,944	6,944
R-squared	0.26	0.08	0.29	0.29	0.11	0.21
Number of municipalities	496	496	496	496	496	496

Each column represents a separate regression. Our dependent variables are the log of total crime rate, auto theft rate, drug dealing rate, murder rate, car theft rate and violent crime rate. We control for population density, log of GDP per capita, and proportion of youths aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 14 years old. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Our robustness tests indicate that our results remain significant and positive in magnitude. Even when we use a crime rate, our estimates remain with the same sign. The same is true for the results by gender. In this case, a shorter period of our panel also maintained the positive results. The use of control variables did not affect our estimates in both cases either. Finally, we added private school enrollments to our variable. The estimates, once again, remained with positive magnitude. Therefore, we provide even more evidence that our results are consistent and that the policy has a positive relation on crime.

6 CONCLUSION

This thesis aimed to analyze the correlation of education on juvenile crime by exploring a change in compulsory schooling law passed in Brazil in 2006. The law transformed the last year of preschool into the first year of elementary school. As a result, new students enter school at age six instead of seven. We argue that the change in the curriculum, which altered the content taught in this grade, allowed students to learn academic skills earlier instead of just focusing on socialization and playing. This gave all students more time to learn the content, making it more understandable to everyone. This reflects throughout the student's elementary education and it decreases the chances of failing and dropping out of school. Students more engaged in school increase their opportunity costs in committing delinquent behavior because the benefits that education provides are more valued.

We analyze the relation of this policy in the state of Rio Grande do Sul. This state presents the best conditions for the estimates, both in relation to the criminal database and the aspect of the program coverage in the municipalities. We estimate a panel between 2004 and 2017 using a treatment intensity variable that measures the proportion of 14 years old students covered by the reform in each municipality. We argue that these students were exposed to the new academic curriculum in the first grade of elementary school.

Our estimates point to an increase in the reported crime for this age. The findings indicate that the exposure to reform increases auto thefts committed by 14-year-olds. An increase on one percentage point in the proportion of treated students is related to an increase of 0.21% on the number of auto thefts. The relation between the policy and total crime, drug dealing, murder, car theft and violent crime is not significant. The addition of control variables seem to not change our main results. We also estimate the correlation for other ages to check if it persists. In all cases the magnitude was significant and with positive sign. An interesting aspect was that the magnitude and type of delinquent behavior varies with age. Older youths tend to become more involved in drug dealing. The robustness tests showed that the relation of the policy remained significant and with a positive signal across all specifications. This provides strong evidence that the relation of the policy on juvenile crime is indeed positive.

The effects of educational policies can be positive on criminal outcomes and that depends on incentives related to opportunity costs. Individuals with lower opportunity costs in crime may have higher incentives to commit them because they understand that returns in the formal market may have little advantage. Education can also encourage crime. This can happen through interaction between crime-prone youths in the same environment, such as in school, for example. This interaction can form delinquent groups that act within the school, around it or elsewhere. They can also encourage other individuals to commit crime, both by forcing them and by influencing them. Our estimates may be capturing that.

We consider that our results are still preliminary and capture a correlation between the new policy and juvenile crime. Further estimates that identify causality in the relationship between these variables and the use of zero inflated models constitute the next steps in this thesis.

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APPENDICES

Table 14 – Estimates for the log of number of total crime.

Variables	(1)	(2)	(3)	(4)
Prop	0.07	0.11	0.10	0.10
	(0.20)	(0.21)	(0.21)	(0.20)
Population density		0.00*	0.00*	0.00*
		(0.00)	(0.00)	(0.00)
GDP per capita			-0.16	-0.15
			(0.20)	(0.20)
Proportion aged 14				11.34
				(9.39)
Constant	0.31**	-1.08	0.51	0.23
	(0.15)	(0.85)	(1.91)	(1.89)
Observations	6,944	6,944	6,944	6,944
R-squared	0.25	0.26	0.26	0.26
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of total crime committed by 14-year-olds. We control for population density, log of GDP per capita, and proportion of youths aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 14 years old. *** p<0.01, ** p<0.05, * p<0.1.

Table 15 – Estimates for the log of number of auto thefts.

Variables	(1)	(2)	(3)	(4)
Prop	0.22**	0.21**	0.21**	0.21**
	(0.10)	(0.09)	(0.09)	(0.09)
Population density		-0.00*	-0.00*	-0.00*
		(0.00)	(0.00)	(0.00)
GDP per capita			0.07	0.07
			(0.05)	(0.05)
Proportion aged 14				0.43
				(2.03)
Constant	0.05	0.53**	-0.20	-0.21
	(0.03)	(0.24)	(0.45)	(0.44)
Observations	6,944	6,944	6,944	6,944
R-squared	0.07	0.08	0.08	0.08
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of auto thefts committed by 14-year-olds. We control for population density, log of GDP per capita, and proportion of youths aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 14 years old. *** p<0.01, ** p<0.05, * p<0.1.

Table 16 – Estimates for the log of number of drug dealing.

Variables	(1)	(2)	(3)	(4)
Prop	0.06	0.09	0.08	0.08
	(0.21)	(0.22)	(0.22)	(0.21)
Population density		0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)
GDP per capita			-0.22	-0.21
			(0.18)	(0.18)
Proportion aged 14				14.18
				(9.07)
Constant	0.22*	-1.05	1.18	0.82
	(0.13)	(0.91)	(1.91)	(1.87)
Observations	6,944	6,944	6,944	6,944
R-squared	0.28	0.29	0.29	0.29
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of drug deealing committed by 14-year-olds. We control for population density, log of GDP per capita, and proportion of youths aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 14 years old. *** p<0.01, ** p<0.05, * p<0.1.

Table 17 – Estimates for the log of number of robbery.

Variables	(1)	(2)	(3)	(4)
Prop	-0.12	-0.10	-0.10	-0.10
	(0.14)	(0.10)	(0.10)	(0.10)
Population density		0.00**	0.00**	0.00**
		(0.00)	(0.00)	(0.00)
GDP per capita			0.03	0.03
			(0.06)	(0.06)
Proportion aged 14				-1.65
				(2.74)
Constant	0.04	-0.83*	-1.09	-1.05
	(0.09)	(0.49)	(0.94)	(0.93)
Observations	6,944	6,944	6,944	6,944
R-squared	0.09	0.11	0.11	0.11
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of robbery committed by 14-year-olds. We control for population density, log of GDP per capita, and proportion of youths aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 14 years old. *** p<0.01, ** p<0.05, * p<0.1.

Table 18 – Estimates for the log of number of murder.

Variables	(1)	(2)	(3)	(4)
Prop	-0.37	-0.31	-0.31	-0.31
	(0.35)	(0.23)	(0.24)	(0.24)
Population density		0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)
GDP per capita			-0.05	-0.05
			(0.09)	(0.09)
Proportion aged 14				3.41
				(4.80)
Constant	0.03	-2.35	-1.83	-1.91
	(0.04)	(1.58)	(1.68)	(1.67)
Observations	6,944	6,944	6,944	6,944
R-squared	0.20	0.29	0.29	0.29
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of murder committed by 14-year-olds. We control for population density, log of GDP per capita, and proportion of youths aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 14 years old. *** p<0.01, ** p<0.05, * p<0.1.

Table 19 – Estimates for the log of number of violent crime.

Variables	(1)	(2)	(3)	(4)
Prop	-0.28	-0.23	-0.23	-0.23
	(0.29)	(0.20)	(0.20)	(0.20)
Population density		0.00*	0.00*	0.00*
		(0.00)	(0.00)	(0.00)
GDP per capita			-0.01	-0.01
			(0.08)	(0.08)
Proportion aged 14				0.30
				(3.87)
Constant	0.05	-1.89	-1.83	-1.84
	(0.11)	(1.22)	(1.66)	(1.65)
Observations	6,944	6,944	6,944	6,944
R-squared	0.16	0.21	0.21	0.21
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of violent crime committed by 14-year-olds. We control for population density, log of GDP per capita, and proportion of youths aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 14 years old. *** p<0.01, ** p<0.05, * p<0.1.

Table 20 – Males: estimates for the log of number of total crime.

Variables	(1)	(2)	(3)	(4)
prop	0.23	0.24	0.22	0.23
	(0.27)	(0.28)	(0.28)	(0.27)
dens		0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)
pib_perc_defla			-0.33	-0.32
			(0.22)	(0.22)
propjovens				21.99
				(16.87)
Constant	0.44***	-0.04	3.37	3.07
	(0.10)	(0.89)	(2.33)	(2.32)
Observations	5,456	5,456	5,456	5,456
R-squared	0.17	0.17	0.18	0.18
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of total crime committed by 14-year-old males. We control for population density, log of GDP per capita, and proportion of males aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old males. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 21 – Males: estimates for the log of number of auto thefts.

Variables	(1)	(2)	(3)	(4)
Prop	0.21**	0.20**	0.20**	0.20**
	(0.08)	(0.08)	(0.08)	(0.08)
Population density		-0.00**	-0.00**	-0.00**
		(0.00)	(0.00)	(0.00)
GDP per capita			0.01	0.01
			(0.05)	(0.05)
Proportion aged 14				-3.90
				(4.43)
Constant	0.02	0.42**	0.30	0.35
	(0.03)	(0.19)	(0.54)	(0.53)
Observations	5,456	5,456	5,456	5,456
R-squared	0.07	0.08	0.08	0.08
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of auto thefts committed by 14-year-old males. We control for population density, log of GDP per capita, and proportion of males aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old males. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 22 – Males: estimates for the log of number of drug dealing.

Variables	(1)	(2)	(3)	(4)
Prop	0.20	0.21	0.18	0.19
	(0.29)	(0.31)	(0.30)	(0.29)
Population density		0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)
GDP per capita			-0.30	-0.29
			(0.19)	(0.19)
Proportion aged 14				22.67
				(15.17)
Constant	0.32***	0.02	3.20	2.90
	(0.11)	(0.79)	(2.02)	(2.00)
Observations	5,456	5,456	5,456	5,456
R-squared	0.17	0.17	0.18	0.18
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of drug dealing committed by 14-year-old males. We control for population density, log of GDP per capita, and proportion of males aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old males. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 23 – Males: estimates for the log of number of robbery.

Variables	(1)	(2)	(3)	(4)
Prop	-0.10	-0.08	-0.09	-0.09
	(0.14)	(0.10)	(0.11)	(0.11)
Population density		0.00**	0.00**	0.00**
		(0.00)	(0.00)	(0.00)
GDP per capita			-0.09	-0.09
			(0.08)	(0.08)
Proportion aged 14				-0.33
				(5.23)
Constant	0.23***	-0.51*	0.42	0.42
	(0.07)	(0.30)	(0.85)	(0.84)
Observations	5,456	5,456	5,456	5,456
R-squared	0.09	0.10	0.10	0.10
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of robbery committed by 14-year-old males. We control for population density, log of GDP per capita, and proportion of males aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old males. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 24 – Males: estimates for the log of number of murder.

Variables	(1)	(2)	(3)	(4)
Prop	-0.38	-0.32	-0.33	-0.33
	(0.35)	(0.23)	(0.23)	(0.23)
Population density		0.00*	0.00	0.00
		(0.00)	(0.00)	(0.00)
GDP per capita			-0.09	-0.08
			(0.13)	(0.12)
Proportion aged 14				6.97
				(8.43)
Constant	0.04	-2.46	-1.56	-1.65
	(0.05)	(1.55)	(2.00)	(1.98)
Observations	5,456	5,456	5,456	5,456
R-squared	0.19	0.29	0.29	0.29
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of murders committed by 14-year-old males. We control for population density, log of GDP per capita, and proportion of males aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old males. *** p<0.01, ** p<0.05, * p<0.1.

Table 25 – Males: estimates for the log of number of violent crime.

Variables	(1)	(2)	(3)	(4)
Prop	-0.24	-0.20	-0.21	-0.21
	(0.27)	(0.18)	(0.18)	(0.18)
Population density		0.00*	0.00*	0.00*
		(0.00)	(0.00)	(0.00)
GDP per capita			-0.15	-0.15
			(0.14)	(0.14)
Proportion aged 14				5.82
				(7.89)
Constant	0.25***	-1.59*	-0.01	-0.09
	(0.05)	(0.96)	(1.62)	(1.58)
Observations	5,456	5,456	5,456	5,456
R-squared	0.16	0.21	0.21	0.21
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of violent crime committed by 14-year-old males. We control for population density, log of GDP per capita, and proportion of males aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old males. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 26 – Females: Estimates for the log of number of total crime.

Variables	(1)	(2)	(3)	(4)
Prop	0.00	0.01	0.01	0.01
	(0.07)	(0.07)	(0.07)	(0.07)
Population density		0.00***	0.00***	0.00***
		(0.00)	(0.00)	(0.00)
GDP per capita			0.00	0.00
			(0.16)	(0.15)
Proportion aged 14				6.45
				(8.19)
Constant	0.19***	-0.45**	-0.47	-0.54
	(0.05)	(0.20)	(1.70)	(1.66)
Observations	5,456	5,456	5,456	5,456
R-squared	0.05	0.05	0.05	0.06
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of total crime committed by 14-year-old females. We control for population density, log of GDP per capita, and proportion of females aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old females. *** p<0.01, ** p<0.05, * p<0.1.

Table 27 – Females: Estimates for the log of number of auto theft.

Variables	(1)	(2)	(3)	(4)
Prop	0.06*	0.06**	0.06**	0.06**
	(0.03)	(0.03)	(0.03)	(0.03)
Population density		-0.00	-0.00	-0.00
		(0.00)	(0.00)	(0.00)
GDP per capita			0.02	0.02
			(0.01)	(0.01)
Proportion aged 14				3.47
				(2.17)
Constant	-0.00	0.13	-0.03	-0.07
	(0.01)	(0.08)	(0.12)	(0.12)
Observations	5,456	5,456	5,456	5,456
R-squared	0.13	0.13	0.13	0.13
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of auto thefts committed by 14-year-old females. We control for population density, log of GDP per capita, and proportion of females aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old females. *** p<0.01, ** p<0.05, * p<0.1.

Table 28 – Females: Estimates for the log of number of drug dealing.

Variables	(1)	(2)	(3)	(4)
Prop	0.04	0.05	0.05	0.05
	(0.09)	(0.10)	(0.10)	(0.10)
Population density		0.00*	0.00*	0.00*
		(0.00)	(0.00)	(0.00)
GDP per capita			0.02	0.03
			(0.11)	(0.11)
Proportion aged 14				5.72
				(7.56)
Constant	0.15***	-0.30	-0.56	-0.62
	(0.04)	(0.24)	(1.24)	(1.20)
Observations	5,456	5,456	5,456	5,456
R-squared	0.06	0.06	0.06	0.06
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of drug dealing committed by 14-year-old females. We control for population density, log of GDP per capita, and proportion of females aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old females. *** p<0.01, ** p<0.05, * p<0.1.

Table 29 – Females: Estimates for the log of number of robbery.

Variables	(1)	(2)	(3)	(4)
prop	-0.03	-0.03	-0.03	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)
dens		0.00	-0.00	-0.00
		(0.00)	(0.00)	(0.00)
pib_perc_defla			-0.04	-0.04
			(0.06)	(0.06)
propjovens				-0.68
				(1.76)
Constant	0.03	0.02	0.43	0.43
	(0.03)	(0.02)	(0.62)	(0.61)
Observations	5,456	5,456	5,456	5,456
R-squared	0.03	0.03	0.03	0.03
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of robbery committed by 14-year-old females. We control for population density, log of GDP per capita, and proportion of females aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old females. *** p<0.01, ** p<0.05, * p<0.1.

Table 30 – Females: Estimates for the log of number of murder.

Variables	(1)	(2)	(3)	(4)
Prop	-0.14	-0.14	-0.14	-0.14
	(0.13)	(0.10)	(0.10)	(0.10)
Population density		0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)
GDP per capita			0.01	0.01
			(0.02)	(0.02)
Proportion aged 14				-0.47
				(1.36)
Constant	0.01***	-0.51	-0.63	-0.62
	(0.00)	(0.36)	(0.50)	(0.50)
Observations	5,456	5,456	5,456	5,456
R-squared	0.14	0.19	0.19	0.19
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of murders committed by 14-year-old females. We control for population density, log of GDP per capita, and proportion of females aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old females. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 31 – Females: Estimates for the log of number of violent crime.

Variables	(1)	(2)	(3)	(4)
Prop	-0.17	-0.16	-0.16	-0.16
	(0.13)	(0.10)	(0.10)	(0.10)
Population density		0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)
GDP per capita			-0.03	-0.03
			(0.05)	(0.05)
Proportion aged 14				-1.15
				(2.34)
Constant	0.04*	-0.49	-0.20	-0.19
	(0.03)	(0.35)	(0.70)	(0.68)
Observations	5,456	5,456	5,456	5,456
R-squared	0.09	0.12	0.13	0.13
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of number of violent crime committed by 14-year-old females. We control for population density, log of GDP per capita, and proportion of females aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old females. *** p<0.01, ** p<0.05, * p<0.1.

Table 32 – Estimates for the log of total crime rate.

Variables	(1)	(2)	(3)	(4)
Prop	0.72	0.72	0.75	0.75
	(1.31)	(1.33)	(1.31)	(1.32)
Population density		-0.00	0.00	0.00
		(0.01)	(0.01)	(0.01)
GDP per capita			0.59	0.58
			(1.14)	(1.13)
Proportion aged 14				-23.12
				(66.07)
Constant	-4.00***	-3.76	-9.67	-9.08
	(0.49)	(4.97)	(11.42)	(11.09)
Observations	6,944	6,944	6,944	6,944
R-squared	0.14	0.14	0.14	0.14
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of total crime rate committed by 14-year-olds. We control for population density, log of GDP per capita, and proportion of youths aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 14 years old. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 33 – Estimates for the log of auto theft rate.

Variables	(1)	(2)	(3)	(4)
Prop	3.11**	2.89**	2.94**	2.94**
	(1.38)	(1.20)	(1.20)	(1.19)
Population density		-0.01*	-0.01*	-0.01*
		(0.01)	(0.01)	(0.01)
GDP per capita			1.06	1.02
			(0.66)	(0.66)
Proportion aged 14				-70.08**
				(30.38)
Constant	-6.42***	1.86	-8.82	-7.05
	(0.53)	(3.96)	(5.47)	(5.40)
Observations	6,944	6,944	6,944	6,944
R-squared	0.07	0.08	0.08	0.08
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of auto theft rate committed by 14-year-olds. We control for population density, log of GDP per capita, and proportion of youths aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 14 years old. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 34 – Estimates for the log of drug dealing rate.

Variables	(1)	(2)	(3)	(4)
Prop	1.21	1.23	1.19	1.19
	(1.36)	(1.39)	(1.37)	(1.37)
Population density		0.00	0.00	0.00
		(0.01)	(0.01)	(0.01)
GDP per capita			-0.72	-0.70
			(1.52)	(1.51)
Proportion aged 14				24.99
				(66.70)
Constant	-5.12***	-5.65	1.57	0.94
	(0.48)	(7.12)	(16.50)	(15.96)
Observations	6,944	6,944	6,944	6,944
R-squared	0.20	0.20	0.20	0.20
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of drug dealing rate committed by 14-year-olds. We control for population density, log of GDP per capita, and proportion of youths aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 14 years old. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 35 – Estimates for the log of robbery rate.

Variables	(1)	(2)	(3)	(4)
Prop	-0.43	-0.22	-0.19	-0.19
	(1.48)	(1.13)	(1.11)	(1.11)
Population density		0.01*	0.01*	0.01
		(0.01)	(0.01)	(0.01)
GDP per capita			0.60	0.55
			(0.88)	(0.87)
Proportion aged 14				-83.73**
				(36.06)
Constant	-6.70***	-14.50***	-20.50*	-18.38
	(0.95)	(5.52)	(11.96)	(11.93)
Observations	6,944	6,944	6,944	6,944
R-squared	0.07	0.08	0.08	0.08
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of robbery rate committed by 14-year-olds. We control for population density, log of GDP per capita, and proportion of youths aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 14 years old. *** p<0.01, ** p<0.05, * p<0.1.

Table 36 – Estimates for the log of murder rate.

Variables	(1)	(2)	(3)	(4)
Prop	-2.06	-1.66	-1.70	-1.70
	(2.21)	(1.58)	(1.58)	(1.58)
Population density		0.02*	0.02	0.02
		(0.01)	(0.01)	(0.01)
GDP per capita			-0.73	-0.74
			(1.00)	(1.00)
Proportion aged 14				-23.75
				(54.43)
Constant	-7.07***	-22.29**	-14.97	-14.37
	(0.44)	(9.37)	(12.45)	(12.16)
Observations	6,944	6,944	6,944	6,944
R-squared	0.20	0.23	0.23	0.23
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of murder rate committed by 14-year-olds. We control for population density, log of GDP per capita, and proportion of youths aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 14 years old. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 37 – Estimates for the log of violent crime rate.

Variables	(1)	(2)	(3)	(4)
Prop	0.42	0.55	0.56	0.56
	(1.20)	(1.07)	(1.04)	(1.04)
Population density		0.01	0.01	0.01
		(0.00)	(0.00)	(0.00)
GDP per capita			0.30	0.27
			(1.24)	(1.23)
Proportion aged 14				-59.09
				(42.28)
Constant	-6.76***	-11.53***	-14.53	-13.03
	(1.06)	(3.95)	(13.55)	(13.37)
Observations	6,944	6,944	6,944	6,944
R-squared	0.10	0.11	0.11	0.11
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of violent crime rate committed by 14-year-olds. We control for population density, log of GDP per capita, and proportion of youths aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population aged 14 years old. *** p<0.01, ** p<0.05, * p<0.1.

Table 38 – Females: estimates for the log of total crime rate.

Variables	(1)	(2)	(3)	(4)
Prop	0.70	0.79	0.80	0.80
	(0.96)	(1.03)	(1.03)	(1.04)
Population density		0.01	0.01	0.01
		(0.01)	(0.01)	(0.01)
GDP per capita			0.18	0.17
			(2.38)	(2.38)
Proportion aged 14				-83.72
				(138.32)
Constant	-4.23***	-10.20**	-12.10	-11.19
	(0.43)	(4.38)	(26.53)	(25.91)
Observations	5,456	5,456	5,456	5,456
R-squared	0.03	0.04	0.04	0.04
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of total crime rate committed by 14-year-old females. We control for population density, log of GDP per capita, and proportion of females aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old females. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 39 – Females: estimates for the log of auto theft rate.

Variables	(1)	(2)	(3)	(4)
Prop	1.02**	0.98**	1.01**	1.01**
	(0.51)	(0.46)	(0.46)	(0.46)
Population density		-0.00	-0.00	-0.00
		(0.00)	(0.00)	(0.00)
GDP per capita			0.39**	0.38*
			(0.19)	(0.19)
Proportion aged 14				-111.45***
				(37.64)
Constant	-6.48***	-4.17***	-8.24***	-7.04***
	(0.17)	(1.30)	(1.93)	(1.89)
Observations	5,456	5,456	5,456	5,456
R-squared	0.12	0.13	0.13	0.13
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of auto theft rate committed by 14-year-old females. We control for population density, log of GDP per capita, and proportion of males aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old females. *** p<0.01, ** p<0.05, * p<0.1.

Table 40 – Females: estimates for the log of drug dealing rate.

Variables	(1)	(2)	(3)	(4)
Prop	0.50	0.59	0.64	0.64
	(1.11)	(1.20)	(1.20)	(1.21)
Population density		0.01	0.01	0.01
		(0.01)	(0.01)	(0.01)
GDP per capita			0.73	0.72
			(1.55)	(1.55)
Proportion aged 14				-99.27
				(128.76)
Constant	-4.60***	-10.36**	-18.02	-16.94
	(0.37)	(4.51)	(17.99)	(17.57)
Observations	5,456	5,456	5,456	5,456
R-squared	0.05	0.05	0.05	0.05
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of drug dealing rate committed by 14-year-old females. We control for population density, log of GDP per capita, and proportion of females aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old females. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 41 – Females: estimates for the log of robbery rate

Variables	(1)	(2)	(3)	(4)
Prop	-0.29	-0.30	-0.33	-0.33
	(0.25)	(0.25)	(0.27)	(0.26)
Population density		-0.00	-0.00	-0.00
		(0.00)	(0.00)	(0.00)
GDP per capita			-0.56	-0.58
			(0.95)	(0.95)
Proportion aged 14				-172.42***
				(25.15)
Constant	-6.14***	-5.97***	-0.13	1.73
	(0.30)	(0.24)	(9.95)	(9.79)
Observations	5,456	5,456	5,456	5,456
R-squared	0.03	0.03	0.03	0.05
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of robbery rate committed by 14-year-old females. We control for population density, log of GDP per capita, and proportion of females aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old females. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 42 – Females: estimates for the log of murder rate.

Variables	(1)	(2)	(3)	(4)
Prop	-2.36	-2.23	-2.21	-2.21
	(2.12)	(1.70)	(1.69)	(1.69)
Population density		0.01	0.01	0.01
		(0.01)	(0.01)	(0.01)
GDP per capita			0.32	0.30
			(0.36)	(0.34)
Proportion aged 14				-177.00***
				(25.50)
Constant	-6.23***	-14.80**	-18.13**	-16.22*
	(0.04)	(6.11)	(8.53)	(8.36)
Observations	5,456	5,456	5,456	5,456
R-squared	0.14	0.19	0.19	0.19
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of murder rate committed by 14-year-old females. We control for population density, log of GDP per capita, and proportion of females aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old females. *** p<0.01, ** p<0.05, * p<0.1.

Table 43 – Females: estimates for the log of violent crime rate.

Variables	(1)	(2)	(3)	(4)
Prop	-2.69	-2.55	-2.58	-2.58
	(2.09)	(1.68)	(1.68)	(1.67)
Population density		0.01	0.01	0.01
		(0.01)	(0.01)	(0.01)
GDP per capita			-0.38	-0.40
			(0.83)	(0.82)
Proportion aged 14				-180.28***
				(36.41)
Constant	-5.90***	-14.51**	-10.55	-8.60
	(0.30)	(5.91)	(11.35)	(11.10)
Observations	5,456	5,456	5,456	5,456
R-squared	0.10	0.14	0.14	0.14
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of violent crime rate committed by 14-year-old females. We control for population density, log of GDP per capita, and proportion of females aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old females. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 44 – Males: estimates for the log of total crime rate.

Variables	(1)	(2)	(3)	(4)
Prop	1.70	1.57	1.58	1.54
	(1.51)	(1.45)	(1.44)	(1.44)
Population density		-0.01	-0.01	-0.01
		(0.01)	(0.01)	(0.01)
GDP per capita			0.03	-0.01
			(1.02)	(1.00)
Proportion aged 14				-87.40
				(118.56)
Constant	-3.12***	2.26	1.90	3.09
	(0.56)	(7.26)	(13.50)	(12.97)
Observations	5,456	5,456	5,456	5,456
R-squared	0.10	0.10	0.10	0.10
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of total crime rate committed by 14-year-old males. We control for population density, log of GDP per capita, and proportion of males aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old males. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 45 – Males: estimates for the log of auto theft rate.

Variables	(1)	(2)	(3)	(4)
Prop	3.20***	3.04***	3.06***	2.96***
	(1.14)	(1.13)	(1.12)	(1.08)
Population density		-0.01**	-0.01**	-0.01**
		(0.00)	(0.00)	(0.00)
GDP per capita			0.33	0.22
			(0.74)	(0.73)
Proportion aged 14				-244.89***
				(62.33)
Constant	-6.29***	1.13	-2.33	0.99
	(0.41)	(3.12)	(8.44)	(8.42)
Observations	5,456	5,456	5,456	5,456
R-squared	0.08	0.09	0.09	0.10
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of auto theft rate committed by 14-year-old males. We control for population density, log of GDP per capita, and proportion of males aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old males. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 46 – Males: estimates for the log of drug dealing rate.

Variables	(1)	(2)	(3)	(4)
Prop	1.76	1.64	1.61	1.59
	(1.54)	(1.48)	(1.47)	(1.45)
Population density		-0.01	-0.01	-0.01
		(0.01)	(0.01)	(0.01)
GDP per capita			-0.54	-0.56
			(1.04)	(1.03)
Proportion aged 14				-31.32
				(114.33)
Constant	-3.86***	1.11	6.78	7.20
	(0.59)	(7.22)	(14.41)	(13.84)
Observations	5,456	5,456	5,456	5,456
R-squared	0.10	0.10	0.10	0.10
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of drug dealing rate committed by 14-year-old males. We control for population density, log of GDP per capita, and proportion of males aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old males. *** p<0.01, ** p<0.05, * p<0.1.

Table 47 – Males: estimates for the log of robbery rate.

Variables	(1)	(2)	(3)	(4)
Prop	0.01	0.16	0.08	0.00
	(1.51)	(1.21)	(1.25)	(1.24)
Population density		0.01*	0.01	0.01
		(0.01)	(0.01)	(0.01)
GDP per capita			-1.11	-1.20
			(1.11)	(1.10)
Proportion aged 14				-190.63***
				(64.64)
Constant	-4.48***	-11.37***	0.26	2.84
	(0.56)	(3.50)	(11.70)	(11.54)
Observations	5,456	5,456	5,456	5,456
R-squared	0.06	0.07	0.07	0.07
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of robbery rate committed by 14-year-old males. We control for population density, log of GDP per capita, and proportion of males aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old males. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 48 – Males: estimates for the log of murder rate.

Variables	(1)	(2)	(3)	(4)
Prop	-2.10	-1.74	-1.83	-1.87
	(2.19)	(1.58)	(1.58)	(1.57)
Population density		0.02*	0.02*	0.02*
		(0.01)	(0.01)	(0.01)
GDP per capita			-1.22	-1.26
			(1.56)	(1.55)
Proportion aged 14				-87.96
				(91.61)
Constant	-6.29***	-21.89**	-9.09	-7.90
	(0.57)	(8.74)	(18.32)	(18.07)
Observations	5,456	5,456	5,456	5,456
R-squared	0.18	0.21	0.22	0.22
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of murder rate committed by 14-year-old males. We control for population density, log of GDP per capita, and proportion of males aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old males. *** p<0.01, ** p<0.05, * p<0.1.

Table 49 – Males: estimates for the log of violent crime rate.

Variables	(1)	(2)	(3)	(4)
Prop	0.92	0.99	0.87	0.83
	(1.00)	(0.94)	(0.90)	(0.91)
Population density		0.00	0.00	0.00
		(0.01)	(0.01)	(0.01)
GDP per capita			-1.71	-1.76
			(1.60)	(1.59)
Proportion aged 14				-108.77
				(86.20)
Constant	-4.58***	-7.92**	10.00	11.48
	(0.47)	(3.89)	(17.78)	(17.81)
Observations	5,456	5,456	5,456	5,456
R-squared	0.10	0.10	0.10	0.10
Number of municipalities	496	496	496	496

Each column represents a separate regression. Our dependent variable is the log of violent crime rate committed by 14-year-old males. We control for population density, log of GDP per capita, and proportion of males aged 14 years old. Standard errors clustered at the municipal level. Robust standard errors in parentheses. Regressions weighted by municipal population of 14 years old males. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.