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On the Relationship Between School Dropouts and Crime in the Netherlands

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Bachelor Thesis

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August 25, 2017

Rotterdam, the Netherlands

Abstract

This bachelor thesis investigates the relationship between school dropouts and contemporaneous crime in the Netherlands between 2005 and 2011. To do this, fixed effects models with municipality level data are exploited. The results indicate that there is a positive relationship between school dropout rates and both property and violent crime in large municipalities. On the contrary, there appears to be no statistically significant relationship in middle-sized and small municipalities. More specifically, a twofold increase of the dropout rate in large municipalities is associated with an approximately 20.6 percent increase in contemporaneous property crime rate, *ceteris paribus*. An equivalent increase of the dropout rate in large municipalities leads to a close to 2 percent increase in violent crime rate, all else equal. Despite its limitations, this paper acts as a stepping stone for further research regarding the causes of the dropout-crime relationship. Additionally, it gives a better idea of the types of crime dropouts in the Netherlands are associated with, in the hope that it will help policy makers in their attempt to reduce these.

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I. Introduction

Over the past years, crime in the Netherlands has been decreasing and so has the number of dropouts. Naturally, one might wonder if this is coincidental or if the two events are correlated. By looking at the figure below, the latter seems likely.

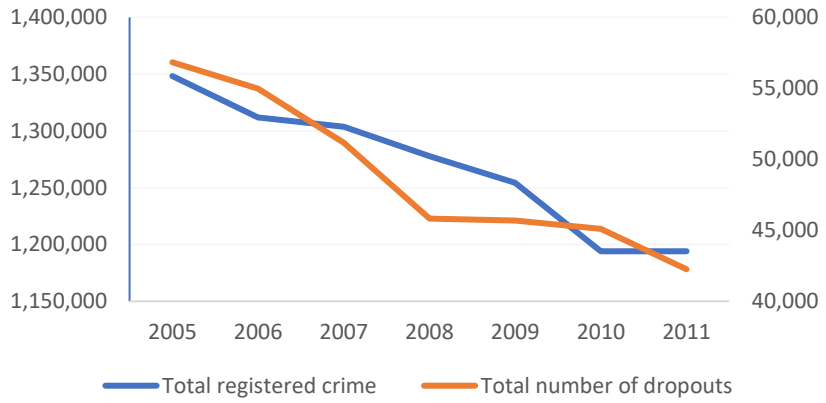

Figure 1. Total registered crime and total number of dropouts in the Netherlands between 2005 and 2011.

This paper attempts to estimate a relationship between dropout rate and contemporaneous crime with the expectation being that individuals who quit school will have more time in their disposal, making them more likely to engage in criminal activity. In other words, I attempt to answer the following research question:

> **What is the relationship between school dropout rate and contemporaneous crime rate in the Netherlands between 2005 and 2011?**

To help answer this research question, two specific hypotheses are tested. The first hypothesis is that there is a positive relationship between school dropout rate and contemporaneous property crime in the Netherlands between 2005 and 2011. The second one states that there is a negative relationship between school dropout rate and contemporaneous violent crime in the Netherlands between 2005 and 2011.

To test the two hypotheses and thereby answer the research question, a fixed effects model with municipality level parameters is exploited. The baseline results suggest that, all else equal, a 100 percent increase in the dropout rate of municipality *m* is associated with a 5.6 percent increase in *m*'s property crime rate. Additionally, a 100 percent increase in dropout rate is estimated to increase violent crime rate in the same municipality by approximately 1.3 percent, *ceteris paribus.* However, these results

quickly become irrelevant when a control for large municipalities is added to the model. The new results indicate a positive relationship between dropout rate and both types of crime in large municipalities between 2005 and 2011, but not in middle-sized and small municipalities. More specifically, regarding the first hypothesis, a doubling of the dropout rate in a large municipality approximately leads to a 20.6 percent increase in property crime rate in that same municipality, *ceteris paribus.* Regarding the second hypothesis, the model indicates that a 100 percent increase of the dropout rate in large municipalities leads to a close to 2 percent increase in violent crime rate, *ceteris paribus*. There appears to be no statistically significant relationship between dropout rate and either types of crime in middle-sized and small municipalities.

As not a lot of previous literature has focussed on this topic, and especially not in the Netherlands, this paper fills a hole in the academic literature. For the most part, research has concentrated on estimating a relationship between years of education and subsequent crime. Only few papers have attempted to find a link between dropouts and crime at the municipality level, and even less have done so in a Dutch setting. Aside from academic relevance this paper also has societal relevance, mainly through its policy implications. Since dropouts are positively correlated to crime in large municipalities, policy makers should consider tackling dropout rates when they want to reduce crime. As there is typically a higher crime rate in large municipalities, this paper's findings can prove to be particularly relevant.

The paper proceeds as follows. Section II presents the theoretical framework, where the economic theory and current state of empirical research on the relationship between education and crime is discussed. Section III describes the data used in this analysis. Section IV presents the identification strategy, followed by the empirical results and a sensitivity analysis, in sections V and VI, respectively. Section VII discusses the results and section VIII concludes.

II. Theoretical Framework

The relationship between education and crime is one that has been widely researched. For the most part, this empirical research focuses on the effects of educational attainment on subsequent crime. Only few papers study the effect of school attendance on contemporaneous crime and even less do so in the Netherlands. This section begins with an explanation of the economic theory behind the relationship of education and crime, as discussed by various academics. I then go on to discuss the current state of empirical research on this relationship and finally, I examine the empirical research on the relationship between school dropouts and crime.

A. The economics of education and crime

It is economically appealing that education is negatively correlated to crime. Lochner and Moretti (2004) discuss two main reasons why this should be the case. Firstly, as wages increase with education ((Freeman, 1996); (Gould, Weinberg, & Mustard, 2002); (Machin & Meghir, 2004)), opportunity costs of committing crimes increase, for two reasons. First, since doing legitimate work after having been educated provides a relatively high wage, the expected returns from committing crime must be significantly higher to risk getting detained for it, thereby decreasing the willingness to commit crime. Secondly, higher wage rates increase the opportunity cost of spending time in prison, further decreasing the incentive to commit crime. The second reason for the negative effect of education on crime, according to Lochner and Moretti, is that school may affect the individuals' level of patience, risk aversion and social networks which indirectly influence their decision to commit crime. In his later paper, Lochner (2007) argues that since criminal behaviour provides direct benefits, only patient individuals will attend school, as the benefits thereof can only be reaped in the future. He further argues that since, according to various economists, returns from school are risky, risk averse individuals will drop out of school. Considering that these dropouts do not have a school degree, their expected wage in the future will be low, making crime an attractive option. Additionally, dropouts might surround themselves with negative peers which consequently might aggravate criminal activity.

B. Empirical evidence of education and crime

There is an abundance of papers that estimate a negative correlation between educational attainment and subsequent criminal activity. Buonanno and Leonida (2006) use panel data to study 20 Italian regions in the period of 1980 to 1995 and discover that education is negatively correlated to crime. More specifically, they regress property crime rate, theft rate and total crime rate on education (measured as average years of schooling of the population), average regional wage and percentage of crimes committed by unknown offenders. They measure this last variable as the ratio of crimes committed by unknown offenders to all recorded crimes in each category and include it as a proxy for the probability of apprehension, with the intuition being that the higher this percentage is, the lower is the probability of getting caught, and therefore the higher the expected returns from crime. Their results suggest that education is negatively (and significantly) correlated to every classification of crime rate, which is in line with their initial expectations.

Lochner and Moretti (2004) use a similar econometric approach in their attempt to estimate the effect of education on arrest rates among men over the age of 18 in the US. They reduce the endogeneity bias in their regressions by using changes in state-specific compulsory schooling laws as an instrumental variable for education, with the intuition being that changes in compulsory schooling laws are

uncorrelated to all factors that affect the decision to commit crime. They use individual-level data on incarceration and schooling and find that a one-year increase in average years of schooling reduces both property and violent crime by about 11 percent. Again, these results are in line with the formed expectations based on economic theory.

One recent paper that attempts to estimate the effect of school attendance on contemporaneous crime is that by Jacob and Lefgren (2003). They estimate a relationship between active school days and crime, by regressing juvenile crime, which is divided in property and violent crime, on the binary variable "No school". Their results indicate that property crime decreases when school is in session, whilst on the contrary, violent crime increases when school is in session. The authors argue that the effect on property crime, called the incapacitation effect, is because school keeps the youngsters busy, leaving them with less time to commit this type of crime. The opposite effect on violent crime, called the concentration effect, is accounted for by the fact that school increases the interaction between youngsters, and therefore also the violent interactions.

A very similar study is carried out by Jeremy Luallen (2006) who also tries to estimate the effect of school attendance on contemporaneous crime. Just like Jacob and Lefgren (2003), his results show that property crimes committed by youngsters decreases with school attendance while violent crime increases with school attendance.

In the Netherlands, the relationship between skipping school and engaging in crime has been studied as early as the 1980s. Research conducted by Junger-Tas *et al.* (1983) suggests that 93 percent of juveniles who often skip school engage in some sort of criminal activity, contrary to approximately 50 percent of youngsters who never skip school. A more recent paper written by Beker and Maas (1998) studying seven thousand students in the Netherlands, concludes that students who frequently skip school are involved in crime twice as often as students who never skip school.

C. Empirical evidence of dropouts and crime

As mentioned previously, a lot less research has been conducted with the purpose of estimating the relationship between school dropouts and criminal activity. The most well-known research to date is the book Delinquency and Dropout written by Elliot and Voss (1974), in which 2617 students enrolled in eight schools in California are followed for four years. The results of their study show that high school dropouts have approximately four times more encounters with the police than non-dropouts. This suggests a positive relationship between dropping out and committing crime, which goes in line with economic theory and past literature on the relationship between education and crime.

Thornberry et al. (1985) argue that there are two contradictory theories regarding the relationship between high school dropouts and subsequent crime, both supported by empirical research. Strain theory suggests that dropping out of high school should be negatively correlated to crime, whilst the social control theory predicts the opposite. Due to the contradictory findings, the authors attempt to improve the methodology of previous research by estimating short and long-term effects separately and taking the age of the dropouts into account. Their analysis suggests that criminal behaviour increases both within one year after having dropped out as well as in the long run, thus rejecting the strain theory.

One of the few papers that attempts to study the effect of dropouts on contemporaneous crime is that by Anderson (2014). The author exploits the variation in minimum dropout age (MDA) laws in the United States to study the effect of staying longer in school on contemporaneous juvenile crime. By using the variation in MDA laws, this analysis focuses on the marginal individual who is obliged to stay in school for longer and would otherwise drop out. The results indicate that an increase in the MDA reduces both property and violent crime rates among high-school aged students. In other words, the author estimates a positive relationship between dropping out and committing both types of crime, supporting the incapacitation but contradicting the concentration effects of school suggested by Jacob and Lefgren (2003).

Blom *et al*. (2005), study the differences in characteristics (such as ethnicity, age and possession of high school degree) between registered crime suspects in the Netherlands. Their conclusion is that individuals between the ages of 18 and 19 without a high school degree have encounters with the police more often than individuals with a degree.

To sum everything up, economic theory predicts a negative relationship between education and crime. Logically, this implies a positive relationship between dropping out of school and committing crime. Indeed, empirical research carried out on the relationship between education and subsequent crime confirms the economic theory and so does most of the research on the effect of dropping out on crime. Interestingly however, when studying education and contemporaneous crime Jacob and Lefgren (2003) and Luallen (2006) estimate 2 different effects; a negative effect of school attendance on property crime and a positive effect of school attendance on violent crime.

III. Data

A. Dataset

A yearly panel dataset at the municipality level in the Netherlands studying the period 2005 – 2011 is constructed to perform the analysis in this paper.

All crime statistics are obtained from Statistics Netherlands (CBS), which is a governmental organisation that collects statistical information about the whole country. In fact, this data consists of registered crime and is separated into many different categories, the relevant ones of which I have aggregated and split into two broader types: property crime and violent crime. Property crimes include: theft/embezzlement, burglary, destruction of property (private and public) and arson (including explosion). Violent crimes include: (public) violence against a person and sexual offences.

Even though I am studying the period 2005-2011, the crime data is provided according to the municipal classification of 2015. In 2005 there were 467 municipalities while ten years later, in 2015, there were only 393 left. This means that in the period studied, some municipalities existed which later did not, as they merged with other municipalities. Since the CBS provides crime data according to the 2015 classification, they have added all the crime committed in those municipalities that merged, to the municipality they later joined. Essentially this means that the municipalities in the 2005-2011 period are treated as if they had already merged back then, even though some of them really merged between 2011 and 2015.

To calculate the crime rates, I divided the number of crimes by the average population of the corresponding municipality and year. Due to the various municipality mergers through the years however, population data for a few municipalities is not available, making my sample "unbalanced". Even though this loss of observations decreases the efficiency of the analysis, Stata can deal with unbalanced data so it does not pose a threat to the significance of the results.

Data concerning school dropouts is obtained from the website of Dienst Uitvoering Onderwijs (DUO), which is part of the Dutch Ministry of Education, Culture and Science. School dropouts are defined as all the individuals between the ages of 12 and 23 that leave education without having obtained a diploma in at least the MBO-2, HAVO or VWO level of the Dutch education system[1].

The data concerning school dropouts is reported based on the 2013 municipal classification. For it to be comparable to the crime data however, it must be adjusted to the 2015 classification. This is done by removing the municipalities that are "lost" and adding the corresponding dropouts to the municipalities

[1] The exact definition of school dropouts (in Dutch) used by DUO can be found on their website through this link: https://duo.nl/open_onderwijsdata/databestanden/vschoolverlaten/

that they merged with. In addition, I divide the number of dropouts by the number of school participants for each municipality and year to obtain the dropout rate, which is this study's main variable of interest.

Aside from the dropout rate there are three additional explanatory variables which act as controls: one lag of dropout rate, average disposable income and one lag of average resolved crime rate. Disposable income is defined as an individual's yearly gross income measured in thousands of euros, reduced by current transfers, income and medical insurance premiums and income and capital taxes. Resolved crimes are defined as crimes for which at least one suspect involved is known to the police, even if they are on the run or deny involvement. Both average disposable income and average resolved crime rate are retrieved from CBS.

There are two reasons for specifically studying the period 2005-2011. Firstly, there is no available school dropout data at the municipality level prior to 2005, to my knowledge. Secondly, DUO altered the method of calculating school dropouts from 2012 onwards. According to them, the new measurement is more precise, making it impossible to compare the data before and after 2011. It must be noted that when the more precise measurement process was implemented, it appeared that the data prior to 2012 was slightly overstated. This could lead to an amplified relationship between dropouts and crime, as is explained in the discussion section. Moreover, the registered crime data until 2011 is classified as definitive, while the data from 2012 onwards is preliminary. An advantage of using definitive rather than preliminary figures is that the latter is subject to change, in which case the relevance of this study would decrease.

B. Descriptive Statistics

To get a better idea of the variables used for the analysis of this study, descriptive statistics are provided in table 1, below.

Table 1. Descriptive Statistics

	Observations	Mean	SD	Minimum	Maximum
Dropout Rate	2765	0.032	0.01	0	0.088
Property Crime Rate	2644	0.041	0.017	0	0.119
Violent Crime Rate	2644	0.006	0.002	0	0.019
Average Disposable Income	2658	14.363	1.772	8.9	24.9
L1.Average Resolved Crime Rate	2765	0.364	0.08	0.139	0.66

Notes: Average disposable income is measured in thousands of euros.

As shown in the table above, not only does the population vary greatly through time and across municipalities, but so do the dropout rate, property crime rate and violent crime rate. We can see that the average dropout rate across the municipalities is approximately 3.2 percent with the maximum

reaching 8.8 percent. The average property crime rate is 4.1 percent, which is almost 7 times higher than the average violent crime rate. Some municipalities experience no violent crimes in certain years, whilst the highest rate in the period studied approaches 2 percent.

Table 2 below, presents the characteristics of the municipalities with the highest and lowest dropout rates in the sample.

Table 2. Top and bottom 10 municipalities in terms of dropout rates

Municipality	Province	Year	Dropout rate	Average Population	Property crime rate	Violent crime rate	Average disposable income	L1.Average resolved crime rate
Panel A: Top 10 municipalities								
Pekela	GR	2010	0.088	13,004	0.037	0.01	12	0.399
Amsterdam	NH	2005	0.078	742,927	0.108	0.012	13.3	-
Rotterdam	ZH	2006	0.074	586,378	0.088	0.015	12.6	0.363
s-Gravehage	ZH	2005	0.071	473,862	0.008	0.009	12.9	-
Lelystad	FL	2007	0.067	72,658	0.055	0.01	13.3	0.407
Utrecht	UT	2006	0.064	284,675	0.119	0.011	13.7	0.282
Tilburg	NB	2006	0.063	200,820	0.007	0.013	12.6	0.317
Schiedam	ZH	2005	0.063	75,438	0.006	0.011	12.2	-
Heerlen	LB	2005	0.063	92,021	0.008	0.011	11.9	-
Schiermonnikoog	FR	2010	0.063	950	0.002	0	14.3	0.647
Panel B: Bottom 10 municipalities								
Schiermonnikoog	FR	2011	0	945	0.037	0.005	15	0.428
Vlieland	FR	2011	0	1,128	0.084	0.009	14.8	0.31
Rozendaal	GD	2008	0.006	1,513	0.043	0.003	23.1	0.519
Sint Anthonis	NB	2008	0.006	11,788	0.026	0.005	14.4	0.438
Tubbergen	OV	2009	0.007	21,069	0.015	0.002	13.2	0.55
Littenseradiel	FR	2010	0.007	10,961	0.01	0.001	13.7	0.306
Ameland	FR	2011	0.007	3,515	0.032	0.004	13.3	0.604
Oirschot	NB	2011	0.008	17,853	0.038	0.005	15.3	0.353
Dinkelland	OV	2011	0.01	26,070	0.017	0.003	14	0.326
Bedum	GR	2008	0.01	10,506	0.026	0.005	13.6	0.358

Notes: GR: Groningen, NH: Noord-Holland, ZH: Zuid-Holland, FL:Flevoland, UT:Utrecht, NB:Noord-Brabant LB: Limburg, FR: Friesland, GD: Gelderland, OV: Overijsel.

The most obvious difference between panels A and B (other than the dropout rate) is the population size. The average population of panel A is approximately 254,000, whereas that of panel B is close to 10,500. In fact, only two out of the top ten municipalities have average populations below 70,000. In contrast, the highest average population in the bottom ten municipalities is just above 26,000. Another, perhaps less obvious difference between the two panels is the violent crime rate. The average rate in municipalities with the highest dropout rates is approximately two times higher than that of the bottom municipalities. The average disposable income is on average higher in panel B than panel A.

Considering that this paper analyses approximately 390 municipalities, providing separate descriptive statistics for each of them would be unnecessarily exhaustive. Moreover, examining how the variables change over the years is more relevant for this study than comparing the municipalities to each other. Therefore, appendix table A1 provides the descriptive statistics per year.

Now that the data has been presented, the next step is to examine the underlying relationship between the variables in the model. Below, the correlation matrix presents this relationship.

Table 3. Correlation Matrix

	Property crime rate	Violent crime rate	Dropout rate	L1.Dropout rate	Average disposable income	L1.Average resolved crime rate
Property crime rate	1.0000					
Violent crime rate	0.7627 (0.000)***	1.0000				
Dropout rate	0.5864 (0.000)***	0.6152 (0.000)***	1.0000			
L1.Dropout rate	0.5941 (0.000)***	0.6195 (0.000)***	0.7808 (0.000)***	1.0000		
Average disposable income	0.1045 (0.000)***	-0.1606 (0.000)***	-0.1133 (0.000)***	-0.0414 (0.048)***	1.0000	
L1.Average resolved crime rate	-0.2019 (0.000)***	-0.0998 (0.000)***	-0.0997 (0.000)***	-0.1228 (0.000)***	-0.1164 (0.000)***	1.0000

Notes: Significance level is reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Surprisingly, a strongly positive relationship is suggested between dropout rate and violent crime rate. This does not go in line with previous literature. The relationship between dropout rate and property crime rate also appears to be positive, which does go in line with previous expectations. Furthermore, there seems to be a positive relationship between the average disposable income and property crime rate, while its relationship with all other variables is negative. Finally, as expected, the average resolved crime rate seems to correlate negatively to both property and violent crime rate.

The correlation matrix gives an idea of the relationships of the selected variables in isolation. To disentangle the impact of each variable separately we rely on regressions, which are presented in the next section.

IV. Identification Strategy

The aim of this analysis is to answer the following research question: What is the relationship between school dropout rate and contemporaneous crime rate in the Netherlands between 2005 and 2011? To help answer it I have formulated two hypotheses, namely:

H1: There is a positive relationship between school dropout rate and contemporaneous property crime in the Netherlands between 2005 and 2011.

H2: There is a negative relationship between school dropout rate and contemporaneous violent crime in the Netherlands between 2005 and 2011.

Following Jacob and Lefgren (2003) and Luallen (2006), I expect that there is a positive relationship between school dropout rate and contemporaneous property crime. This can be explained by the incapacitation effect of school, which suggests that as school keeps youngsters busy, their time and opportunities to commit crime decrease. On the other hand, the expected negative relationship between dropout rate and contemporaneous violent crime can be explained by the concentration effect of school. This effect suggests that keeping juveniles in school increases their interactions with each other and therefore also the possible conflicts between them. The baseline empirical models used to test the two hypotheses can be described in the following way:

$$Property\ crime\ rate_{m,t} = \alpha_m + \beta_1 dropout\ rate_{m,t} + \beta_2 dropout\ rate_{m,t-1} + \beta_3 average\ disposable\ income_{m,t} + \beta 4 average\ resolved\ crime\ rate_{m,t-1} + \varepsilon_{m,t} \quad (1)$$

$$Violent\ crime\ rate_{m,t} = \gamma_m + \delta_1 dropout\ rate_{m,t} + \delta_2 dropout\ rate_{m,t-1} + \delta_3 average\ disposable\ income_{m,t} + \delta 4 average\ resolved\ crime\ rate_{m,t-1} + \eta_{m,t} \quad (2)$$

where the subscripts m and t represent municipality m and year t and $\varepsilon_{m,t}$ and $\eta_{m,t}$ represent the error terms.

The reason for calculating the rates of crime and dropouts rather than just using the absolute numbers is to be able to accurately compare the two variables, as municipalities differ greatly in size. This way the variation in crime that is due to the differences in population is accounted for, so there is no need to further control for municipality size. Apart from the fact that a municipality with a larger population is likely to have a higher number of criminals, another effect is being controlled for here. Typically, there are a lot more things to do in municipalities with large populations (think of cinemas, bars, football stadiums, *et cetera*), which attract more people and therefore plausibly increase opportunities to commit crime.

Although the municipality size is being controlled for, other control variables are required to reduce the risk of omitted variable bias. One lag of dropout rate is included because previous studies have estimated a positive effect of dropouts on subsequent crime (Elliot & Voss (1974); Thornberry *et al.* (1985); Blom *et al.* (2005)), suggesting that some of the variation in crime is due to the variation in past dropout rate. The reason for only using one lag is because more lags of dropout rate decrease the adjusted R-squared and the number of observations used. A lower adjusted R-squared suggests that by adding a second lag, the model explains less of the variation in crime. Using less observations decreases the efficiency of the results.

The average disposable income can be considered as a proxy for the general level of wealth, as well as an indicator for the returns from legitimate labour in each municipality. I expect this variable to influence both property and violent crime.

Following the likes of Buonanno and Leonida (2006), I control for the level of policing in each municipality by including a lag of the average resolved crime rate. The higher this variable is, the higher is the probability of getting apprehended by the police in that municipality, and therefore the lower the expected returns from crime. In other words, this variable captures the variation in crime that is caused by differences in law enforcement. To calculate this rate for a certain year, all crimes that are committed in that same year are taken into account. Therefore, it is impossible for the average resolved crime rate at year t to affect crime at year t, which is why I use one lag. One issue with this variable is that its definition includes the crimes for which suspects are on the run. If a high resolved crime rate includes a lot of crimes for which the criminals are not apprehended, it might not lower their expected returns from crime, as the probability of getting caught has not increased. Nonetheless, I do not expect this to be the case on average, so it should work reasonably well.

These specific explanatory variables are chosen based on intuition, previous literature and data availability. Once the corresponding data was collected, a correlation matrix was constructed to make sure that the independent variables are not very correlated to each other, as this would lead to multicollinearity. Variables other than the lag of dropout rate that have a correlation coefficient of higher than 0.5 are removed, leaving us with the current empirical models. Despite the high correlation

between the dropout rate and its lag, I decided to keep it in the regression as I believe it is relevant and contributes to the validity of this analysis.

These variables all have in common that they are measured at the municipality level. At this level, it is very difficult to find data on other variables that could affect crime, making it challenging to further reduce omitted variable bias. Therefore, it must be noted that even though estimating a causal relationship between the variables of interest would be ideal, it is realistically not attainable in this analysis. To my knowledge, most of the previous studies that attempt to estimate something similar do this using data at the individual level, where a lot more variables that can influence crime are available. Nonetheless, as Allison (2009) explains, one way to get closer to causality is by exploiting a fixed effects model. After running a Hausman test to decide whether to use a random effects or a fixed effects model, the latter was chosen[2]. This model controls for time-invariant unobserved municipality characteristics, capturing them by the constant term (α_m and γ_m). The estimated coefficients can therefore not be biased due to omitted time-invariant characteristics, bringing us one step closer to the "true" effect that we are aiming for. One general drawback of this estimation technique is that it does not show the coefficients of the fixed municipality specific parameters, making it impossible to observe their effect on crime. This is not an issue for my analysis however, as its purpose is to consistently estimate the effect of dropout rate, which does change over time.

Another alternative is to use a pooled OLS model. This is essentially an OLS technique run on panel data, treating it as if it is cross-sectional. As this is not an adequate technique for this type of data, I do not expect it to perform well. Nevertheless, to determine whether a fixed effects model is more appropriate, both are run and their results are compared in the next section.

The reason for using a linear functional form rather than a logarithmic or quadratic form lies in the scatterplots of the dependent variables on the independent variables. Having plotted these for various years and both models, they all suggest a linear relationship, as shown in appendix figure A1.

Finally, the plots of the residuals versus the fitted values of both regressions shown in appendix figure A2 indicate that the standard errors do not have a constant variance, violating a central linear regression assumption. To account for this, robust standard errors are used which assure that the errors of the regression output are valid despite the heteroscedasticity.

[2] The results of the Hausman specification test can be found in appendix table A2.

V. Empirical Results

Table 4 shows the pooled OLS and fixed effects estimates for property crime rate and violent crime rate. The dependent variable in models 1 to 4 is property crime rate, while the dependent variable in models 5 to 8 is violent crime rate. Columns labelled as (a) indicate the results for the basic specifications, where no control variables are present. Columns marked as (b) show the results after controlling for the stated parameters.

As mentioned previously, pooled OLS is an OLS technique run on panel data, treating it as if it is cross-sectional which is fundamentally wrong. Therefore, when using the pooled OLS estimation method I expect to obtain inaccurate estimates. Additionally, when no controls are included in the regression (models 1 and 5) I expect the already miscalculated coefficients to be biased due to omitting relevant variables. In other words, I do not expect crime, whether it is property or violent crime, to only be caused by dropouts; this is impossible. Therefore, it must be that the dropout rate estimate is overstated for both types of crime. Even when adding controls however (models 2 and 6), both estimated coefficients of dropout rate are unrealistically high.

The fixed effects estimation method controls for municipality specific unobserved fixed effects. By doing so, a lot of variables that are omitted in models 1 and 2 are now being controlled for. But even when controlling for these and one variable that changes over time, as model 3 and 7 do, omitted variable bias will most likely still be an issue. Therefore, the fixed effects models that control for various relevant variables are expected to produce the most consistent estimates (models 4 and 8).

Examining the results for the first hypothesis we can see that indeed, the dropout rate estimates of models 1 and 2 seem to be biased. The coefficient in model 1 suggests that, all else equal, if the dropout rate doubles, the property crime rate will increase by about 97 percent. This almost one-to-one relationship is highly improbable. The dropout rate estimate of model 2 supports this idea as it drops to 0.533 when more parameters are included in the regression.

The coefficient estimated by the fixed effects model without control variables drops even further to 0.2335. Even though this looks more realistic than models 1 and 2, model 4 seems to be the best for this analysis, as it controls for relevant parameters. The estimated coefficient of dropout rate for this model is 0.0563 and it is marginally statistically significant. This estimate suggests that, all else equal, a twofold increase in the dropout rate is associated with an approximately 5.6 percent increase in property crime rate in the same municipality. The lag of dropout rate is also statistically significant and has a stronger positive effect on property crime rate, suggesting that property crime is more affected by dropouts in the previous period than dropouts in the same period. Finally, both the average disposable income and the lag of average resolved crime rate seem to have a small, negative effect on property crime.

Table 4. Estimation Results: Pooled OLS and Fixed effects

	Property crime rate				Violent crime rate			
	Pooled OLS		Fixed effects		Pooled OLS		Fixed effects	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Dropout rate	0.9718	0.533	0.2335	0.0563	0.1565	0.0889	0.03	0.0129
	(0.0346)***	(0.0620)***	(0.0314)***	(0.0297)*	(0.046)***	(0.0077)***	(0.0044)***	(0.0059)***
L1.Dropout rate		0.5451		0.0664		0.0859		0.0138
		(0.0584)***		(0.0247)***		(0.0071)***		(0.0044)***
Average disposable income		0.0016		-0.0018		-0.0002		-0.0003
		(0.0002)***		(0.0003)***		(0.0000)***		(0.0001)***
L1.Average resolved crime rate		-0.0244		-0.0069		-0.0015		-0.0008
		(0.0035)***		(0.0014)***		(0.0005)***		(0.0003)***
Constant	0.0103	-0.0088	0.0337	0.0658	0.0008	0.0039	0.0048	0.0089
	(0.0011)***	(0.003)***	(0.001)***	(0.0051)***	(0.0001)***	(0.0004)***	(0.0001)***	(0.001)***
R-squared	0.3438	0.4382	0.0652	0.1082	0.3785	0.4536	0.0398	0.0881
Observations	2644	2271	2644	2271	2644	2271	2644	2271

Notes: Standard errors are reported in parentheses. Standard errors are robust to heteroscedasticity. The R-squared value reported for the fixed effects models indicate the within R-squared. ***, ** and * indicate coefficient significance at the 1%, 5% and 10% level, respectively.

Furthermore, the within R-squared value of model 4 suggests that approximately 10.8 percent of the variation in crime rate can be explained by the model. We are looking at the within R-squared because we are only interested in how the model explains variation in the property crime rate within a municipality, not between municipalities.

Turning to the results of the second hypothesis, a similar pattern is observed in models 5 and 6 as in 1 and 2. The estimated effect of dropout rate on violent crime rate is most likely biased in both pooled OLS models, leaving models 7 and 8 to be more trustworthy. As no other parameters are included in model 7, I expect model 8 to provide the most consistent estimates.

The statistically significant coefficient in this model suggests that a doubling of the school dropout rate is related to a, on average, 1.29 percent increase in violent crime rate, *ceteris paribus*. Just as for property crime rate, one lag of dropout rate appears to have a larger effect on violent crime rate than dropout rate in the same period. This suggests that the relationship between dropouts and subsequent violent crime is slightly stronger than that with contemporaneous violent crime. The estimate of average disposable income suggests that, other things held constant, if it increases by 1000 euros per year, violent crime rate will decrease by approximately 0.0003 percentage points; a truly small, yet statistically significant effect. The estimate of one lag of average resolved crime rate also appears to be weakly negatively correlated to violent crime rate. Furthermore, the model explains approximately 8.8 percent of the variation in violent crime rate, a little bit less than the explanatory power of model 4.

VI. Sensitivity Analysis

One concern in the preceding analysis is that the effect of dropout rate on crime is different in big municipalities than in middle sized and small municipalities. As mentioned before, there are typically a lot more opportunities to commit crime as well as a lot more distractions from school in large municipalities. The combination of these two factors could lead to a different effect of dropouts on crime in large municipalities than in non-large municipalities.

To test whether this is indeed the case, I include two additional parameters in both baseline regressions. The first one is “large municipality”, a dummy variable which takes the value of 1 if the municipality is large and 0 otherwise and the second one is an interaction term between dropout rate and “large municipality”. The dummy variable controls for differences between large and non-large municipalities, whereas the interaction term differentiates between the effect of dropout rate in a large municipality and its effect in a non-large municipality, on crime.

Of course, whether a municipality is considered large is relative to the size of the other municipalities. I define a large municipality as one which has an average population of at least 40,000 inhabitants. By

this definition approximately 30 percent of all municipalities in the dataset are classified as large. This threshold is chosen based on the definition of large municipalities used by the Dutch Ministry of Social Affairs and Employment in a 2016 publication[3].

As I expect the fixed effects model with controls to give the most consistent estimates in my baseline analysis, I use the same estimation method in this section. The linear regressions can be described in the following way:

$$Property\ crime\ rate_{m,t} = \lambda_m + \zeta_1 dropout\ rate_{m,t} + \zeta_2 dropout\ rate_{m,t-1} + \zeta_3 (dropout\ rate * large\ municipality)_{m,t} + \zeta_4 average\ disposable\ income_{m,t} + \zeta_5 average\ resolved\ crime\ rate_{m,t-1} + \zeta_6 large\ municipality_{m,t} + \xi_{m,t} \quad (3)$$

$$Violent\ crime\ rate_{m,t} = \theta_m + \mu_1 dropout\ rate_{m,t} + \mu_2 dropout\ rate_{m,t-1} + \mu_3 (dropout\ rate * large\ municipality)_{m,t} + \mu_4 average\ disposable\ income_{m,t} + \mu_5 average\ resolved\ crime\ rate_{m,t-1} + \mu_6 large\ municipality_{m,t} + \omega_{m,t} \quad (4)$$

where the subscripts m and t represent municipality m and year t and $\xi_{m,t}$ and $\omega_{m,t}$ represent the error terms.

Table 5 presents the baseline estimates (models 4 and 8) and the estimates including the new parameters (models 9 and 10). Starting by comparing models 4 and 9, we can see how the estimated effects on property crime rate change, after controlling for large municipalities. When the dummy variable and interaction term are added, the coefficient of dropout rate decreases from 0.0563 to 0.0161. Since the estimate has largely decreased, become statistically insignificant and the coefficient of the interaction term is statistically significant, the model suggests that the effect of dropout rate on property crime rate is only present in big municipalities. Model 9 suggests that a 100 percent increase of the dropout rate in a large municipality is approximately associated with a 20.6 percent increase in property crime rate in that same municipality, *ceteris paribus*. In contrast, we cannot say anything about the effect of the dropout rate in a middle-sized or small municipality, as its coefficient is not statistically different from zero.

A similar pattern can be observed when looking at model 10, where the dependent variable is violent crime rate. After the addition of the two parameters, the dropout rate estimate has decreased from 0.0129

[3] This publication discusses an unemployment benefit distribution system to municipalities. Other than for its definition of large municipalities, the publication is irrelevant for this analysis.

to 0.009 and has become statistically insignificant. This, in combination with the statistically significant coefficient of the interaction term, suggests that the effect of dropout rate on violent crime rate in non-large municipalities is not statistically different from zero. In large municipalities on the other hand, a 100 percent increase in the dropout rate leads to a close to 2 percent increase in violent crime rate, *ceteris paribus*.

Table 5. Estimation results with and without large municipality control: Fixed effects model

	Property crime rate		Violent crime rate	
	Model 4	Model 9	Model 8	Model 10
Dropout rate	0.0563	0.0161	0.0129	0.009
	(0.0297)*	(0.0302)	(0.0059)***	(0.0067)
Dropout rate*Large municipality		0.2062		0.0204
		(0.0681)***		(0.0103)***
Large municipality		-0.0172		-0.0012
		(0.0033)***		(0.0004)***
L1. Dropout rate	0.0664	0.0573	0.0138	0.0128
	(0.0247)***	(0.0241)***	(0.0044)***	(0.0044)***
Average disposable income	-0.0018	-0.0017	-0.0003	-0.0002
	(0.0003)***	(0.0003)***	(0.0001)***	(0.0001)***
L1.Average resolved crime rate	-0.0069	-0.0065	-0.0008	-0.0008
	(0.0014)***	(0.0014)***	(0.0003)***	(0.0003)***
Constant	0.0658	0.0681	0.0089	0.0089
	(0.0051)***	(0.0049)***	(0.001)***	(0.001)***
R-squared	0.1082	0.1379	0.0881	0.093
Observations	2271	2271	2271	2271

Notes: Models 4 and 8 indicate the baseline estimates discussed in the empirical results section. Models 9 and 10 present the results including the dummy for large municipalities and the interaction term. Standard errors are reported in parentheses. Standard errors are robust to heteroscedasticity. The R-squared value reported indicates the within R-squared. ***, ** and * indicate coefficient significance at the 1%, 5% and 10% level, respectively.

One concern that arises when adding the interaction term and the dummy variable is that their estimates might be unreliable due to multicollinearity. As shown in appendix table A3, these two parameters are very correlated, possibly making the estimation of the interaction term coefficients inaccurate. The effect reported should therefore be interpreted with caution.

VII. Discussion

To reiterate, the first hypothesis states that there is a positive relationship between school dropout rate and contemporaneous property crime in the Netherlands between 2005 and 2011. The results presented in the previous section suggest that this is only true for large municipalities. There appears to be no statistically significant relationship between school dropout rate and contemporaneous property crime in middle-sized and small municipalities.

The second hypothesis states that there is a negative relationship between school dropout rate and contemporaneous violent crime in the Netherlands between 2005 and 2011. According to this paper's results, this hypothesis is rejected; there appears to be a relatively weak, positive relationship between school dropout rate and contemporaneous violent crime rate in large municipalities. In contrast, the results suggest no relationship between dropout rate and violent contemporaneous crime in non-large municipalities.

Therefore, to answer the research question concretely, there seems to be a positive relationship between dropout rate and both types of crime in large, Dutch municipalities in the period 2005 to 2011. In contrast, there appears to be no statistically significant relationship in middle-sized and small municipalities between dropout rate and either type of crime.

It must be noted, that since the reported school dropout data is slightly overstated (as mentioned in the data section), the effect of dropouts on crime is probably somewhat upward biased. In other words, the true effect might be smaller than what is suggested by the results. Even though the difference in effects is most likely limited, ignoring it might lead to false conclusions.

Interpreting the estimated relationship as a causal one will also most likely lead to false conclusions. For a relationship to be interpreted as causal, some strong assumptions need to hold. Typically, the most challenging one is exogeneity, as it is fundamentally untestable. Exogeneity implies that nothing in the error term is correlated with the independent variables, or in other words, there is no endogeneity. One source of endogeneity is omitting variables from the model specification that are correlated to both crime and dropouts. Even though testing for this is impossible, it is highly likely that some variables are omitted from the previously discussed specifications. By studying municipality level data, I cannot control for personal characteristics of the dropouts, for example. It is therefore impossible to determine whether it is the act of dropping out of school that causes an increase in crime or if there are underlying characteristics that cause individuals to drop out and to commit crime. To my knowledge, all other research conducted with the purpose of estimating a similar but causal relationship uses individual level data. Nonetheless, one measure that is taken to reduce endogeneity is the use of a fixed effects model. An additional measure would be to use an instrumental variable. Due to time and data availability limitations however, it is not done in this paper.

Despite not being able to estimate a causal relationship, these results do have some policy implications. Since dropping out of school seems to be positively correlated to crime in large municipalities, introducing policies that decrease dropout rates in these municipalities might lead to a reduction in crime. Additionally, as an abundance of research estimates a negative relationship between education and subsequent crime, keeping people in school for longer might also reduce crime in the long term. According to this analysis, such policies would be ineffective in non-large municipalities, where there seems to be no significant relationship.

VIII. Conclusion

Regarding the relationship of school dropout rates and crime in the Netherlands between 2005 and 2011, various things should be considered. Firstly, that it differs for property crimes and for violent crimes. Even though both are positive, it seems like the relation with property crime is stronger than that with violent crime. Secondly, they both appear to hold only in large municipalities. In the rest, no statistically significant relationship is estimated. Just by looking at the baseline results one would conclude that the relationship between dropout rate and crime is relatively weak. This conclusion quickly becomes irrelevant when the effect of dropout rate is differentiated between large and non-large municipalities, however. The effect of dropout rate on property crime rate in large municipalities is estimated to be approximately 4 times stronger than what was suggested by the baseline results. Its effect on violent crime rate in large municipalities is estimated to be double as strong.

Results of other research indicate a negative relationship between education and crime. Since dropping out of school without having obtained a degree implies having less education, a positive relationship of dropout rate and crime is expected. That said, Jacob and Lefgren (2003) and Luallen (2006) estimate a positive relationship between school attendance and violent crime, rather than a negative one. One possible explanation of our contrasting results could lie in the nature of our data. Their research exploits individual level data and juvenile crime rate, whereas in mine, municipality level data and overall crime rate is used. The reason no previous literature uses macro level data to estimate such a relationship, is most likely because of the difficulty to infer causality. Despite this papers' attempts at coming closer to causal estimates, stating that the estimated relationship is a causal one would be misleading.

Nonetheless, this paper acts as a stepping stone for further research regarding the causes behind the relationship of school dropouts and crime, in the Netherlands and abroad. Additionally, this paper's findings give policy makers in the Netherlands a better idea of the types of crime dropouts are associated with, in the hope that it will help them in their attempt to reduce these.

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Appendix

Table A1. Descriptive Statistics 2005-2011

	Observations	Mean	SD	Minimum	Maximum
		Panel A: 2005			
Dropout rate	395	0.037	0.011	0.012	0.078
Property crime rate	370	0.045	0.019	0.004	0.119
Violent crime rate	370	0.006	0.003	0.001	0.019
Average disposable income	371	12.75	1.433	8.9	20.5
L1.Average resolved crime rate	-	-	-	-	-
		Panel B: 2006			
Dropout rate	395	0.036	0.01	0.013	0.074
Property crime rate	372	0.043	0.018	0.014	0.119
Violent crime rate	372	0.006	0.003	0.001	0.019
Average disposable income	376	13.434	1.465	9.4	22.3
L1.Average resolved crime rate	395	0.36	0.084	0.157	0.625
		Panel C: 2007			
Dropout rate	395	0.033	0.01	0.01	0.068
Property crime rate	377	0.042	0.017	0.015	0.108
Violent crime rate	377	0.006	0.003	0.001	0.017
Average disposable income	376	14.523	1.73	10.4	24.9
L1.Average resolved crime rate	395	0.362	0.079	0.14	0.645
		Panel D: 2008			
Dropout rate	395	0.03	0.009	0	0.063
Property crime rate	377	0.041	0.017	0.012	0.107
Violent crime rate	377	0.006	0.003	0	0.016
Average disposable income	378	14.89	1.65	10.7	24
L1.Average resolved crime rate	395	0.361	0.078	0.157	0.588
		Panel E: 2009			
Dropout rate	395	0.03	0.009	0.007	0.061
Property crime rate	379	0.04	0.017	0.012	0.105
Violent crime rate	379	0.006	0.003	0.001	0.015
Average disposable income	382	14.91	1.63	10.6	23.4
L1.Average resolved crime rate	395	0.348	0.082	0.139	0.66
		Panel F: 2010			
Dropout rate	395	0.029	0.01	0.007	0.088
Property crime rate	382	0.038	0.015	0.01	0.096
Violent crime rate	382	0.005	0.002	0	0.014
Average disposable income	387	14.946	1.585	10.8	23.2
L1.Average resolved crime rate	395	0.369	0.079	0.15	0.647
		Panel G: 2011			
Dropout rate	395	0.027	0.008	0	0.057
Property crime rate	387	0.038	0.015	0.01	0.095
Violent crime rate	387	0.005	0.002	0.001	0.016
Average disposable income	388	15.015	1.464	10.9	22.4
L1.Average resolved crime rate	395	0.383	0.076	0.167	0.604

Table A2. Hausman Specification Test

	Coefficients		S.E.
	Fixed	Random	
	Dependent variable: Property crime rate		
Dropout rate	0.0563	0.1851	0.001
L1.Dropout rate	0.0664	0.191	0.0011
Average disposable income	-0.0018	-0.0003	0.0001
L1.Average resolved crime rate	-0.0069	-0.0086	.
Chi2	90.53		
Prob>Chi2	0.0000		
	Dependent variable: Violent crime rate		
Dropout rate	0.0129	0.0321	0.0008
L1.Dropout rate	0.0138	0.0321	0.0008
Average disposable income	-0.0003	-0.0001	0.0000
L1.Average resolved crime rate	-0.0008	0.0001	.
Chi2	1588.23		
Prob>Chi2	0.0000		

Notes: The null hypothesis states that the difference in coefficients is not systematic. Rejecting this hypothesis therefore suggests that it is, and a fixed effects model is preferred over a random effects model.

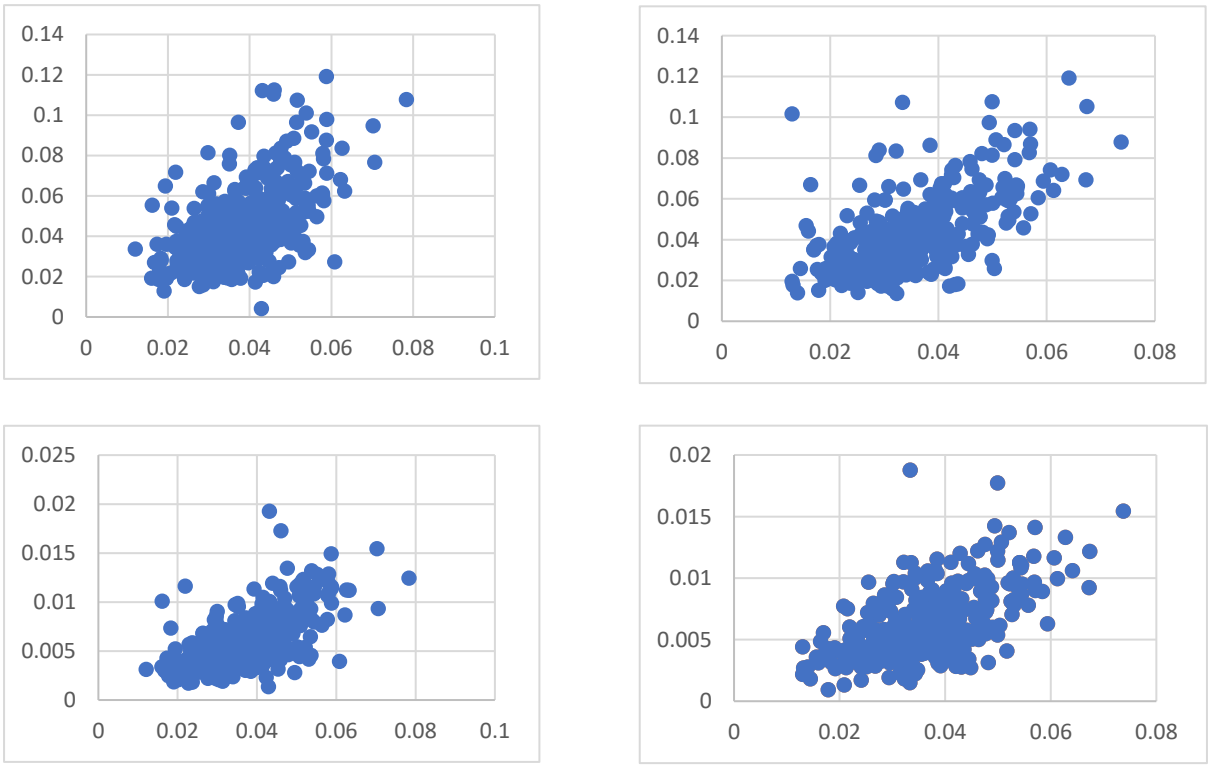

Figure A1: 4 scatterplots indicating the linear relationship between the variables. The top two are scatterplots of property crime rate on dropout rate in 2005 (left) and 2006 (right). The bottom two are scatterplots of violent crime rate on dropout rate in 2005 (left) and 2006 (right). The relationship between these and the rest of the variables in all years is also linear but not included in the appendix as it is unnecessarily exhaustive.

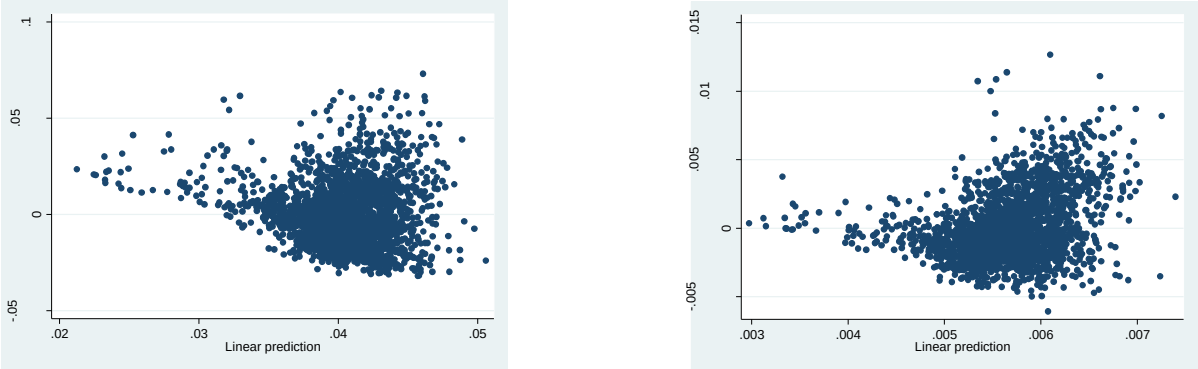

Figure A2: Plots of residuals versus the fitted values. The dependent variable in the left plot is property crime rate. The dependent variable in the plot on the right is violent crime rate. The plots indicate that the standard errors are heteroscedastic; they do not have a constant variance.

Table A3. Correlation Matrix of the Two Additional Parameters

	Property Crime Rate	Violent Crime Rate	Dropout Rate	L1.Dropout Rate	Average Disposable Income	L1.Average Resolved Crime Rate	Big Municipality	Dropout Rate*Big Municipality
Big Municipality	0.5242	0.5280	0.4622	0.4666	-0.0447	-0.1456	1.0000	
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.0217)***	(0.000)***		
Dropout Rate*Big Municipality	0.6045	0.6099	0.5863	0.5717	-0.0746	-0.1511	0.9588	1.0000
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.0001)***	(0.000)***	(0.000)***	

Notes: Significance level is reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The main point of this table is to indicate the very high correlation coefficient of the interaction term with the dummy variable.