PEER EFFECTS IN CLASSROOM:
DO CLASSMATES MATTER FOR YOUR FUTURE?

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ABSTRACT

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Abstract

Peer effect has been a growing target of interest in academic literature. However, measuring these peer effects is hard because of the well-known methodological and data limitations. I study the peer effects in schools and classrooms to examine the impact of disruptive peers on education and criminality[1]. I do this by using a rich school choice data set from Finland combined to different register data sets, which provides criminal, educational and other relevant information about peers and their parents. I use the year-to-year variation of the portion of children who are considered to be disruptive peers and estimate these spill overs by using year, school and class label fixed effects. I find evidence of negative peer effects at a class level, but not at a school level. I find that adding one disruptive peer in a class of 20 people increases the other students' probability to commit a crime by 2 per cent, decreases the probability to get a matriculation examination by 2 per cent and increases the probability of not getting any degree after secondary school by 1,1 per cent. I also find that adding a disruptive boy peer into a class has stronger effect on every outcome than adding a disruptive girl peer. All these estimates are statistically significant.

Key words
peer effect, criminality, education, labor economics

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TIIVISTELMÄ

Tekijä Jussipekka Salo	
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Tiivistelmä Vertaisvaikutukset ovat kasvava kiinnostuksen kohde akateemisessa kirjallisuudessa. Vertaisvaikutusten mittaaminen on kuitenkin hankalaa johtuen rajoitteista tutkimusmenetelmissä ja aineistoissa. Tutkin koulu- ja luokkakavereiden vaikutusta rikollisuuteen ja koulutukseen hyödyntämällä toisen asteen yhteisvalinta-aineistoa[2]. Tutkimukseni kohderyhmä koostuu oppilaista, joiden vanhempi on tuomittu rikoksesta. Yhdistämällä yhteisvalinta-aineistoon Tilastokeskuksen yksilötason rekisteritietoja saan tiedot oppilaiden ja heidän vanhempien rikollisuudesta, koulutuksesta ja muista relevanteista muuttujista. Tutkimuksessani käytän hyväksi kohderyhmän vuositason vaihtelua koulussa sekä luokassa ja estimoin tällaisten opiskelijoiden vaikutuksia käyttäen kiinteiden vaikutusten mallia. Tutkimuksen tulokset osoittavat, että luokkakavereilla on vaikutusta. Yhden kohderyhmän lapsen lisääminen luokkaan, jossa on 20 oppilasta, kasvattaa keskimäärin kahdella prosentilla muiden oppilaiden todennäköisyyttä tehdä rikos, alentaa keskimäärin 1,1 prosentilla todennäköisyyttä suorittaa ylioppilastutkinto sekä lisää keskimäärin kahdella prosentilla todennäköisyyttä sille, ettei luokkakaveri suorita toisen asteen tutkintoa. Tulokset osoittavat myös, että kohderyhmässä poikien vaikutus on tyttöihin verrattuna suurempia jokaisessa selitettävässä muuttujassa. Tulokset ovat tilastollisesti merkitseviä.	
Asiasanat Vertaisvaikutus, rikollisuus, koulutus, työn taloustiede	
Säilytyspaikka Jyväskylän yliopiston kirjasto	

[2] Haluan kiittää Tilastokeskusta aineiston tarjoamisesta, sekä Kristiina Huttusta ja Valtion Taloudellista Tutkimuskeskusta avusta ja hyödyllisistä neuvoista tähän tutkielmaan.

CONTENTS

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1 INTRODUCTION

Do classmates matter for youths' future education and criminality? Motivating social scientists, including economists should not be too hard. If classmates truly matter and are a major factor for driving outcomes like test scores, high school diplomas, employment and criminal activity, then parents, teachers and policy makers will care about these peer effects and the size of them. (Sadercote, 2011)

School is a natural part of individuals' life and children spend most of their days there. The reason why peer effects in school should be investigated broadly is that individuals themselves are affected by their peers, individuals' children are affected by his peers and individuals' family and friends are also affected by their peers. For example, 85 % of the teachers and 73% of parents answered to a nationally representative survey made in the United States that they believed the claim: "school experience of most students suffers at the expense of a few chronic offenders" (Public Agenda, 2004). Basically, if everyone in a society spends most of his childhood time at school and if schoolmates have some effect on others' outcomes, then their schoolmates affect everyone both directly and indirectly.

The effect that peers have on youth's criminal activity and education outcomes has been a growing target of interest in academic literature. Even though this question is highly relevant in economics, it is most of all an interdisciplinary question. This subject is highly interesting in a point of sociology, criminology, psychology and economics, for a few to mention.

Even though there is strong evidence of agglomeration spillovers for criminal behavior the precise causal effect is still unclear (Billings, Ross, Deming, 2016). There are studies which have found that school and peers do matter for criminality and other outcomes, such as test results, earnings, high school graduation and college attendant (Billings et al 2016; Billings, Deming, Rockoff 2014; Carrell and Hoekstra 2010; Carrell, Hoekstra, Kuka 2018). Segregated schools and neighborhoods have been a concerning topic in political conversation which has led to several policy actions, especially in the United States (see Angrist & Lang 2004; Billings et al 2016; Billings et al 2014). Most of the studies have found short-term effects, but not so many studies give evidence from the long run effects of disruptive or ''troubled'' peers. How much do we know so far from the causal effect of peers on criminal activity and education?

I study the peer effects in a Finnish secondary school. If a person A has a classmate or a schoolmate B and B affects the educational or criminal outcome of a person A, I regard this as a peer effect. A peer effect can be either direct or indirect. A direct peer effect happens when the student B does not change A's behavior. For example, the student B can talk in the classroom so loud that the student A cannot hear the teacher. Indirect peer effect occurs when the student B changes the student A's behavior. For example, when the student B breaks the rules often and the student A wants to be like him and starts breaking rules himself. (Sadercote, 2011)

I study the peer effects on education and criminality in a classroom using very rich Finnish school choice datasets, which include all individuals who have graduated from the Finnish secondary school in years 1991-2007. I use the word "secondary school" to identify the 7th to the 9th grades in the Finnish education system. I combine this data set in four different panel data sets. This unique data enables me to follow an individual for eight years after finishing the secondary school with the knowledge of his schoolmates, classmates, background characteristics, criminal - and educational outcomes. The data set includes over 1 million individuals. A really important feature of this data set is that it allows me to identify children whose parents have a criminal record, allowing me to identify potentially "bad apples". This is important, because parents' criminality is exogenous to students' classmates, which resolves the reflection problem (Manski, 1993). Both this study and another studies (Kristoffersen, Krægpøth, Nielsen & Simonsen, 2015) show that parent's criminality is a good proxy for a disruptive peer.

Most datasets do not allow this kind of exogenous way to identify the "quality" of a child and for that reason credible estimation of peer effect has not been an easy task. It is hard to determine whether a child causes his classmates outcomes or do the classmates cause his outcome. However, my identification strategy helps me to deal with this "reflection problem". Additionally there is a possibility that disruptive peers self-select into the same school or some common unobserved attribute affect their future.

I use the year-to-year variation in proportion of disruptive peers to see if it has an effect on school- and classmates' educational and criminal outcomes. That is the main purpose of this paper. I provide empirical test for a "bad apple-model" (Hoxby & Weingarth, 2005), which suggest that some student can harm the learning of others. Using this representative data set I am able to include school, class label and year fixed effects, which helps me to deal with the selection problem.

I find that there are no negative peer effects at a school level, but there are significant peer effects at a class-level. Adding one disruptive peer in a class of 20 people increases the other students' probability to commit a crime by 2 per cent, decreases the probability to get a matriculation examination by 2 per cent and increases the probability of not getting any degree after secondary school by 1,1 per cent. I also find that adding a disruptive boy peer into a class has stronger effect on every outcome than adding a disruptive girl peer.

To make sure that my results hold I offer two falsifications tests and two robustness checks. I do the falsifications tests to make sure that there is no self-selection in schools and classes. I find little evidence of self-selection. My robustness checks show that my estimates hold and that common shocks are not driving my results.

This paper is structured as follows: Section one introduces. Section 2 introduces the theoretical mechanisms, which are relevant in peer effects in education and criminality. Section 3 introduces some selected papers about peer effects in criminality and education. Section 4 presents data and discusses about my identification strategy. Section 5 shows the results. Section 6 discusses about the results and section 7 concludes.

2 THEORETICAL MECHANISM

There is no one right answer to the question: How does a peer affect? The intuition behind this statement is clear. One can think about many different ways that a peer can affect education or criminality. The answer or answers to this question are extremely important in order to identify the mechanisms and use information to make necessary policy if needed. One way of thinking about this question is to separate the channels into two different categories, which are direct effects and indirect effects (Hasan & Bagde, 2013). An indirect channel relies on mechanisms that link peer characteristics to students' preferences, aspirations and beliefs, like affecting one's attitude on schooling or being an example or a role model (Hasan & Bagde, 2013).

A direct channel requires more interaction between peers. It is a channel where a peer affects directly, for example showing how a math exercise is done or telling how some English word should be pronounced. A direct channel implies that peers who are more capable are more useful when one wants to learn (Hasan & Bagde, 2013). In this chapter, I will introduce the most common theories in literature regarding to peer effects in education and criminality. Due to the nature of this question I will introduce many theories and potential mechanisms instead of focusing on one specific.

2.1 Theories for peer effects in education

A Bad apple model is a model which suggests that the presence of a student with poor outcomes would do harm for other students. This student causes large negative spillovers in a several ways: The bad apple peer may cause disorder in the classroom and distract the teacher and other students from producing productive tasks. He may encourage other students in disruptive behavior, directly or indirectly. The negative externalities can also come from the reason that the bad apple does not disturb but he just simply needs more attention because of his bad performing and thereby the teacher has less time for the other students. There are also less students to learn from when bad apples are in the class. This theory is the closest to my strategy, due to the fact that I try to identify a ''disruptive peer'' and see if those peers have an impact on the others educational outcomes. (Hoxby & Weingarth, 2005 ; Sadercote 2011)

The opposite model for a Bad apple is called the shining light model. In this model great performance of one student will lead to better outcomes of other students. In the model a student can help others directly for example helping them to do their exercises or giving them the right answers. A student can also help others indirectly by working a lot and being an example for others. This is an interesting model but it is not very easy to think about the ways how a tremendous student can help the others than it is to think ways a terrible student could harm the others. (Hoxby & Weingarth, 2005 ; Sadercote 2011)

The boutique model suggests that students benefit when they are working with students who have similar abilities as they have. There are few possible mechanisms for this. The first one is quite intuitive: a classroom with more homogeneity enables a teacher to teach with a particular pace and customize material to a particular group. Student can also teach one another and learn from each other. This model seems to be justification behind the tracking in schools by ability. (Hoxby & Weingarth, 2005 ; Sadercote 2011)

A rainbow model is the opposite of the boutique model. It suggests that the diversity of ability is good for all students in the classroom. One logic of this is that students benefit because they learn to answer to a question more deeply when they see many point of views. The model does not explain very well why school uses tracking more or less (for example music classes and sport classes). (Hoxby & Weingarth, 2005 ; Sadercote 2011)

A linear-in means model suggests that students' outcome is a linear function of the mean of peers' outcome. So that if your peers perform well it will increase your performance average as well. This would mean that if there were added one good peer into a classroom at the same time with one bad peer into classroom, the effects would rule each other out. This model has an unpleasant feature, which is that according to this model no form of segregation is stable. All allocations of peers are equally beneficial to aggregating in the model. Because of the fact that certain forms of segregation arise routinely, they are either through another model or due to institutional factors that are consistent and persistent. (Hoxby & Weingarth, 2005 ; Sadercote 2011)

2.2 Theories relevant to peer effects in crime

In criminology literature theories explaining the association between peers and crime are divided into two main categories. Other theories explain the causal mechanisms in this question, while other theories explain it only through a correlation (like social selection). I will focus mainly on those theories that try to explain this peer effect with the causal mechanism, because that is the target of interest in this paper.

The theories related to causal peer effects on crime can be divided into two different categories: learning and group process theories. These theories assume that delinquent peer company is causally related to delinquency, but they differ on the specific mechanisms explaining these relations. (Matsueda & Anderson, 1998).

Before Sutherland's famous differential association theory marked a watershed in criminology in 1939 the best explanation for criminal behavior was the multiple-factor approach. Criminal behavior was determined by different conditions such as age, mental health, alcoholic parents, broken homes and inadequate socialization. Sutherland argued that this multiple-factor approach could not provide scientific understanding for criminal behavior. He argued that different conditions like race and gender can not explain criminality because not all black men do crimes and some white women commits a crime. (Matsueda, 1988, Sutherland 1947)

Differential association theory is a theory, which argues that delinquency results from learning skills and knowledge, favorable to a crime over the ones unfavorable to a crime. This is likely to happen when dealing with a delinquent group rather than groups without delinquency. According to this theory, also the effects of association with delinquent peers are depended on frequency, duration, priority and intension. This means that the more time, greater frequency, closer and earlier association with delinquent peer increases delinquency. Differential association theory says that any structural condition like age or sex affects only to the probability to learn skills and knowledge favorable to a crime, but they do not affect directly to criminality. There is a wide range of criminological research backing up differential association theory. (Matsueda & Anderson, 1998; Moon, Hwang & McCluskey , 2011; Sutherland 1973)

The extension of differential association theory: social learning theory, suggests that criminal peers influence criminality through reinforcement. The learning mechanism in social behavior is through direct conditioning and imitation. People learn when interacting with groups. Groups can modify youth behavior. Groups can modify attitudes, norms and the understanding of good and bad behavior. The behavior can be verbal or cognitive and it can be reinforced directly because of the peer group. (Akers, Krohn, Lanza-Kaduce & Radosevich, 1979; Akers, 1973)

Group process theories argue that connecting with a delinquent peer is causally vis-à-vis delinquent behavior (Matsueda & Anderson, 1998). Delinquent peer groups can offer situationally induced motives, solutions, pressures and acts to an individual (Matsueda & Anderson, 1998). These kinds of situations and mechanisms are easy to understand. One might consider a situation where a boy has been called by names and the group provides solutions and pressure to act back. Another situation might be a situation where a girl "steals" a boy from another girl and the girl who's been hurt wants to get "revenge".

One clearly relevant hypothesis is social selection. This is an example of a theory explaining connection between peers and criminality, but cannot be considered as a causal mechanism. An individual with a delinquent behavior likes to hang out with other individuals who have criminal behavior. This means that criminality increases the probability of association with delinquent peers. It is clear that adolescents with criminal behavior drift to a group, which rewards, doesn't judge, and supports youth's behavior. The opposite, those who are not comfortable with such a behavior probably do not end up hanging out in groups with criminal behavior. This is called social selection. There is a kind of reciprocal effect between the causality hypothesis and social selection. However, it is extremely hard to distinguish the role of social selection from the peer effect. (Matsueda & Anderson, 1998)

Sutherlands stated in 1947 about gang operation:

> It is not possible to determine the extent to which the gang produces criminality. Many gangs are merely organizations of persons, who are, as separate persons, criminalistically inclined.

According to Akers (2013) there is a possibility for the social selection, but he argues that causation is a stronger effect than social selection. (Matsueda & Anderson, 1998; Sutherland, 1947; Akers 2013)

Learning theories implicates that when causality hypothesis and social selection are combined, there is a kind of self-feeding effect. Delinquent peers increase the likelihood of criminality and this increases the likelihood to hang out with criminal peers in the future. Thornberry (1987) integrated this to an "interactional theory". Interactional theory emphasizes reciprocal effects between these two concepts. According to Thornberry (1987) delinquent behavior is related to attachment to parents, delinquent peers, commitment to school, conventional beliefs and delinquent values. These factors affect in different times through adolescence. In early adolescence, delinquency and delinquent peers are affected by relationship to parents. In middle adolescence delinquent values and school commitment drives the impact, in late adolescence it is delinquent values and factors like employment and education that drives the impact. The reciprocal effects between the actual target of interest, delinquency and delinquent peers remains relatively time invariant according to Thornberry (1987). (Thornberry, 1987; Matsueda & Anderson, 1998)

All these theories (theories relevant for peer effects in education and criminality) put together one can understand many different ways why the peers play an important role in youths' outcomes and how peers might affect to youths' criminal and educational behavior. It is clear that potential mechanisms do exist and that these mechanisms can occur at the same time. Theories show that peer effects are a complicated phenomenon and that the major mechanisms stay unclear. Next section provides academic evidence to back up these theories and shows that peer effects are real and they do exist.

3 REVIEW OF EMPIRICAL LITERATURE

There is a wide range of literature regarding peer effects. In this literature review I try to introduce these peer effects in many different perspective and environments.

How much do we know so far about the causal effect of school and peers in criminal activity? In this literature review, I will first go through the main papers of school and criminality and then I will introduce some selected papers of peer effects on criminality and other outcomes. However, I selected more literature that focuses on criminality, because that is the main target of interest. After introducing the papers, I will talk about the main problems of peer effect literature and about the mechanism school and peers' impact on criminality.

3.1 Early studies

A few studies use data from Charlotte-Mecklenburg Schools (CMS) which is 20th biggest school district in the United States (Deming 2011). Ever since the mid-1990s the North Carolina Public Instruction has collected schools' information about the student's achievement, background and attendance (Deming 2011).

In his article *Better school less crime?* Deming combines this data set with arrest and incarceration information from Mecklenburg County and the North Carolina Department of Corrections (NCDOC). Deming studies the impact of the lottery in CMS, where places at oversubscribed schools were admitted by lottery. Deming uses this lottery to identify the causal effect of winning the lottery and not winning the lottery. Every child had guaranteed access to neighborhood school but the parents had a possibility to take apart in this lottery in order to get their child to a better school. The lottery was broad-based and 95% of the parents submitted at least one choice. There were 1891 lottery winners who studied in high school and 2320 in middle school. Over 60% of the winners were black and most of them were from a low income family. The results show that the lottery did reduce adult crime especially for African-American males and males from high-risk quintile. Lottery reduced crime by 50% and had a small impact on behavior but not on performance of high-risk youths. The lottery did not have impact on any test results. Study finds that peer effects explain more of the impact in middle school, whereas school quality is more important in high school. (Deming 2011)

Billings et al. (2013) uses this same CMS data combined to data from National Student Clearinghouse to study how the end of busing affected the educational attainment and crime. The idea is to use new school boundaries because of a policy change by comparing students who live in the same neighborhood but on the opposite side of the new school boundaries. Before the policy, school busing was race-based and after the policy kids attended to their neighborhood school. The redrawing led to an increase in segregation, the share of students attending a middle or high school with a high portion of black student jumped from 12 % to 21% and the share attending comparatively integrated school (where the portion of black students were 35-65%) fell from 53% to 40%. According to Billings et al. (2013) the resegregation of CMS increased inequality of outcomes between minority and white people. Both the white and the black got lower results when they attended schools with more minority students. A 10 percentage points increase in the share of minorities decreased high school test scores by about 0.014 standard deviations and increased the probability of ever being arrested and incarcerated about 1.5 percentage points, which equals about an 8% increase compared to the average of minority males. Billings et al. (2013) argue that white students' probability to graduate from high school and attend a college decreases when they are placed to schools with more minority students. The effect on crime is driven by high portion of minority males being grouped together in both school and neighborhood. (Billings et al. 2013)

Billings et al. (2016) studied the impact of criminal peers on individual's criminal activity. The study uses the data from CMS and combines it with arrest registry data for Mecklenburg County which includes information on the amount and type of charges. It also allows researchers to identify individuals that were arrested for the same crime. About 22 percent of all crimes were committed with one or more peers. The idea of the research is to study that will the increase in the number of similar peers living nearby and studying in the same school make a youth more likely to commit a crime? Researches calculate the number of youths who have the same grade-gender-race within a kilometer and are placed to the same school, comparing the attendance boundaries. The second step was to pair youth offenders living in same neighborhood and in the same school attendance area and study how the probability of criminal partnership varies with distance. They find that one standard deviation (8.3 students) increase in the same school peers (same grade-gender-race) increases the probability of ever being arrested by 3.9 percentage points, which indicates 23% increase in the probability ever being arrested compared to an average student. Being assigned to the same grade and school and living one kilometer by each other, makes individuals six times more likely to form a criminal relationship compared to pairs with different schools. The effects are driven by males (mostly by minority males) and arise only when the individuals are in the same school and live in the same neighborhood. (Billings et al 2016)

Carrell et al. (2018) studies the long-run effect of disruptive peers on labor market consequences. Data is collected by linking data on elementary school students from a Florida county to their educational and earnings records. Data allows identifying children who have suffered from domestic violence. The idea is to find if the portion of these kids in a class affect the others' educational and labor outcomes. They use the natural variation of the portion of disruptive peers in cohort across time within given school to identify the impact of disruptive peers. Adding one disruptive student into a class of 25 in grades 3 to 5 reduces achievement by 0.014 standard deviation. Results show that it is the boys who affect the outcome and from those families that have not yet reported the domestic violence. Adding one disruptive boy to a class of 25 people leads to 1 percentage points decrease in college enrollment and reduces the probability of receiving degree by 2.2 percentage points. Disruptive classmates in elementary school did not have an impact on employment but they did have an impact on earnings. Adding one child who has suffered from domestic violence reduces others' earnings by 3,9 percent and adding one not yet reported domestic violence peer to a class reduces earnings even more, by 5.5 percent. Earnings are measured between the ages of 24 to 28. Carrell et al. (2018) also look at the heterogeneity and they find that students seem to have the same kinds of effect despite gender and socioeconomic status. White students seem to suffer more than black when it comes to earnings and the exposure to disruptive peers have the largest effect on those peers who are from lower income families. (Carrell et. al, 2018)

Carrell & Hoekstra (2010) studies the short-term externalities of children exposed to domestic violence using the same Alachua county data from Florida linked to Alachua County Courthouse data, which gives the opportunity to identify those kids who suffer from domestic violence. They use domestic violence as a proxy for a disruptive peer and they test the effect of portion of these peers in a class, by controlling school, grade, year and other attributes. Their outcome variables are reading scores, math scores and the number of disciplinary incidents. They show that adding one disruptive peer in a class of 20 students will increase the number of disciplinary incidents by 1.86. Researchers also look the heterogeneity of the outcomes and find that the spillovers vary across gender and background and are caused mostly by boys. One additional low-income troubled peer to a class of 20 student decreases the test scores for higher-income student by 1.5 percentage point and increases misbehavior of students from low-income families. Adding one troubled boy to a class of 20 people reduces boys' test scores by 2 percentile points. (Carrell & Hoekstra, 2010)

Jacob & Lefgren (2003) studies the impact of school on juvenile crime from a different point of view. The aim is to find a connection between the school off session and criminal activity. They use teacher in-service days which generates exogenous variation. They combine data by national incident-based reporting system to a calendar of individual school districts. The data reports nature, time and location of the crimes. They measure the juvenile crime in a certain day using teacher in a service as a dependent variable including other off session variables and city-year-month fixed effects. When all crimes are considered, school and crime do not have a connection. However, Jacob & Lefgren (2003) find that school seem to reduce juvenile property crimes by 15 percent but it increases the level of juvenile violent crime by almost 30 percent. (Jacob & Lefgren 2003)

Angrist & Lang (2004) study the impact of Metropolitan Council for Educational Opportunity (Metco), which is a desegregation program. In the program some of the students from Boston schools are send to more wealthy school areas. Parents who want to participate in this program place their child on a waiting list and every year Metco coordinators notify the number of open places and the students will be selected at first-come-first-served basis. Angrist & Lang uses school-level data for Massachusetts (Metco-receiving districts and nearby) and micro data from a large district Brookline which includes data for 1994-2000 school years. The strategy is to measure the differences between Metco students and not Metco students when all other background characteristics equals. They use the class size information to predict whether class receives a Metco student and use this as an instrumental variable to check that their estimates are not biased because of omitted variables, which could arise if school personnel reduce the class size when students are doing poorly or if the Metco students are placed to classes where other students are doing relatively well. The study finds little evidence of Metco students' impact on their non-Metco classmates. They find some evidence for a negative impact of Metco students on the test scores of black third graders. They conclude that the effects of Metco students on non-Metco students are small. (Angrist & Lang, 2004)

Damm & Dustmann (2014) studies the effect of early exposure to neighborhood crime on later criminal behavior. They use data from Denmark in years 1986 and 1998 when refugee immigrants were assigned quasi randomly. They link data from three different sources: the central police register, which records individual crime charges; the administrative registers, which provide individual demographic characteristics and the Educational Institution register and surveys, which contain data on educational performance. The idea is to measure if the number of criminals in the area had impact on refugees' criminal activity. They use the quasi-randomization and municipality fixed effects, while controlling other relevant background characteristics. One standard deviation higher rate of criminals increases the probability of a crime conviction by 4 percent. The results show that it is mostly the youth violent crime conviction rate that affects individual's criminal behavior and it is the share of criminals that has an effect, not the share of criminality. They find that increase in the share of criminals from the same ethnic group increases conviction probabilities of others. They do not find any effect on education. (Damm & Dustmann, 2014)

In their study Bayer, Hjalmarsson, Pozen (2009) investigate the peer effects on juvenile offenders who serve at the same time in the same facility. Their analysis is based on data which covers over 8000 individuals in 169 juvenile facilities in a two-year period. The primary data source is the database maintained by Florida Department of Juvenile justice. The idea is to measure peer by exposure to a particular characteristic by weighting the average as a number of days the individual spends with each peer. They cannot identify the exact set of peers but they assume that the within variation in peer characteristic is random respect to assigned to facility. Researchers include facility and facility-by-prior-offence fixed effects with additional peer characteristics, focusing on crime-specific peer effects. They estimate the recidivism for those who have and have not a prior history of certain crime. They find that peer effect only appears if individual has already committed a certain crime. The results show that one standard deviation increase in exposure to peer increases burglary crime by 0.19, which means that the likelihood of recidivism increases from 13.6% to 16.6%. One standard deviation increase on exposure to peers with drug felony history increases the probability to recidivate from 28.5% to 31.6%. (Bayer, Hjalmarsson, Pozen 2009)

3.2 The main problems in literature

The two main problems when investigating peer effects are reflection problems and selection bias. The reflection problem arises when a child and a peer's outcomes are observed simultaneously, it is hard to separate the effect that a group has on individual from the effect that individual has on group. In another words put: "Does the mirror image cause the person's movements or reflect them?" (Manski, 1993). There are three types of hypotheses to explain common observations of group behavior (Manski, 1993):

1) Endogenous effects, wherein the individual's behavior varies with the behavior of the group.
2) Exogenous effects, wherein the individual's behavior in a group varies with exogenous background.
3) Correlated effects (common shocks), wherein the individual's behavior in a group correlates because of similar characteristic or similar institutional environment.

It is important to recognize these effects, because they have differing policy implications. For example, let's say that a school decides to offer tutoring for those who need it. If individual achievement rises with average achievement, then this tutoring has also indirect impact on others' performance, which is called ''social multiplier''. This happens when behavioral effects are endogenous, not exogenous or correlated. (Manski 1993)

In order to overcome the reflection problem is best to find a proper instrument for peer behavior or ability. Another strategy is to use preexisting measures for peers as proxy, like race (Deming 2011, Billings et al. 2013, Billings et al 2016), school reallocation (Angrist & Lang, 2004) or the attendance of children who have family problems (Carrell & Hoekstra 2010, Carrell et. al, 2018). The last mentioned option solves the reflection problem as long as students' peers do not cause the domestic violence. Using peers' family violence as a exogenous proxy for child quality provides much better measure for peers than using a race or a gender. (Carrell & Hoekstra, 2010)

When an individual self-selects into a peer group (for example hopes classmates) it is impossible to determine whether the outcome is a causal effect of the peers or the reason why individual joined the group (Hoxby, 2002). There are two ways to resolve this problem. The first one is to exploit the random assignment of individuals to peer group (Damm & Dustmann, 2014). As this possibility does not occur very often, other option is to exploit the natural variation of cohorts or classes across time within school. This can be done by using a large panel dataset with a series of fixed effects models, like controlling school-grade-year and all the necessary background characteristics like gender, race, family income etc. There is also concern about common shocks driving the results. This problem is solved by including school-grade linear time trends and controlling school-by-year specific fixed effects. (Carrell & Hoekstra, 2010)

Angrist (2014) raises concerns about negative mechanical correlation between own and peer characteristics when using peer averages as the explanatory variable. The solution for this is separate students who affect and who are affected, for example using domestic violence as a proxy. Angrist (2014) is also concerned about the measurement error leading to bias in peer effect estimates. One way to handle this problem is to add measurement errors and see if they affect the results.

3.3 Mechanisms in early literature

The results show that there is a connection between the environment and criminality. The important question is the following one: what is the causality of this? What is the mechanism of the peers impacting an youth's criminality, school performance, misbehavior, college attendance or even wages? Is the school the reason child is doing better or worse? Is it the quality of teacher, better learning material or the learning peace? One could ask if it is the ''troubled'' peers who make a child do crimes or is it the others who help disruptive peers be less disruptive? Troubled children can affect the other by disrupting them or because there are fewer students to learn from. These questions are highly important in order to guarantee equal possibilities for everyone. In order to make this happen it is important to know the mechanisms, because different mechanisms have different policy implications.

According to Deming (2011) we can assume that it is the peer effect which is more important for the middle school lottery winners because social network formation is very important for teenagers and these peer affects can be underestimated. Lottery applicants are a self-selected group and it is possible that their parents are applying for it because of some specific peers (for example the child can be bullied). These effects would not show on calculations. Deming (2011) also says that it is the quality of school, which is more important for high school lottery winners. The one possible mechanism here is that the reduction in crime comes from the increasing of human capital returns. When attending a better school it will raise the marginal productivity of investments in schooling and that will lead to a higher opportunity cost of crime and incarceration. A similar kind of mechanism is offered by Bayes et al (2009) when investigating peer effects of juveniles. They say that peers who have committed same crime can increase the individual's returns from crime by increasing the human capital through social learning. (Deming 2011, Bayes et al 2009)

Billings et al. (2014) states that it might be the resources that have a connection on results, not only the amount of minorities. Schools with high minority percentages of students might get lower funding compared to schools with low minority percentage. They test this hypothesis and find that indeed the state started to add resources to those schools, which had most minority students and this helped them to get better scores.

According to Billings et al (2016) direct peer interaction is a main mechanism for social multiplier in criminal behavior. This means that if some policy action leads to a higher segregation, it will also lead to a higher crime rate when all else equals. Schools play an important role when forming criminal network. School and neighborhood segregation might be partially responsible for high crime rates in ''bad'' areas. If concentrating these disadvantaged youths together increases the crime rates of these youths and considering that school plays big part of this so called endogenous affect, then the policy should manipulate the school assignment. (Billings et al, 2016)

As mentioned before troubled children can affect the others by disrupting them or because there are fewer students to learn from. Carrell et al. (2010) finds that it is disruption that seems to drive their results. Disruptive peers affect on achievement of children from high-income families and behavior on children from low-income familes. Potential explanation for this could be that children from high-income families are more sensitive for bad behavior and children from low-income families are more accustomed to it. Children from low-income families might be less likely to face consequences at home because of their bad behavior in school.(Carrell & Hoekstra, 2010)

Carrell et.al (2018) expect the effect on earnings coming from peer effect on non-cognitive skills. The researchers also remind that even though it seems that there is a different impact on disruptive peers to high- and low-income families it might be that school and neighborhood sorting causes itself the differences on earnings. This is because of the correlations between domestic violence and low-income. (Carrell et.al, 2018)

Social interaction is a key factor linking neighborhood crime with later criminal behavior. Damm & Dustmann find support for this by studying the outcomes of refugees in Denmark. They find that it is the youth crime conviction rate and not the adult criminal rate, which affects the later criminal behavior. Another finding which supports the social interaction mechanism is that own ethnic group's criminal behavior impacts more than other ethnic group's criminality, because they likely have more communication and interaction opportunities. Researchers repeat that it is the amount of criminals in the area which has an impact on criminal activity, not the amount of crimes committed. (Damm & Dustmann, 2014)

Social interaction is also one possible mechanism that Bayer et al. (2009) offers when investigating the peer effects of prisoners and according to them peers reinforce the addictive behavior. This can be important for example in the case of drug crimes and car thefts. This same mechanism appears in study of Jacob & Lefgren (2003) where they found that school increases the juvenile violent crimes, because the youths have more interaction when they are at school. (Bayes et al 2009, Jacob & Lefgren 2003)

More studies about the schools' and classmates' impact on youths' criminality are welcome. The literature has been mainly focused on the United States and founds from other parts of the world would be welcomed in to existing literature. The consequences of segregation and peer effects are shown in academic literature. The segregation of neighborhoods and schools causes concerns for equality and for these reasons the knowledge provided by academic studies is needed. Especially long-term impacts are not very well known, which leaves questions for future researchers.

TABLE 1 Summary of studies

Study	**Method**	**Strategy**	**Result**
Deming 2011	Fixed effects & IV-method	Deming uses lottery to identify the causal effect of winning the lottery and not winning the lottery.	The lottery reduced adult crime especially for African-American males and males from high-risk quantile. Lottery reduced crime by 50% and had small impact on behavior but not on performance of high-risk youths. The lottery did not have impact on any test results.

(continues)

TABLE 1 Summary of studies

Billings, Deming, Rockoff 2014	Fixed effects	Billings et al. uses new school boundaries by comparing students who live in the same neighborhood but on the opposite side of the new school boundaries.	The resegregation of CMS increased inequality of outcomes between minority and white people. Both the white and the black scored lower results when they attended schools with more minority students. The overall effect on crime is driven by comparatively high portion of minority males being grouped together in both school and neighborhood.
Billings, Ross, Deming, 2016	Fixed effects	Studies the impact of criminal peers on individual's criminal activity. Calculate the number of youths who have the same grade-gender-race within a kilometer and are assigned to the same school, making comparisons across attendance boundaries. The second step was to pair youth offenders living in same neighborhood and in the same school attendance area and study how the probability of criminal partnership varies with distance.	One standard deviation (8.3 students) increase in the same school peers (the same grade-gender-race) increases the probability of ever being arrested by 3.9 percentage points, which indicates 23% increase in the probability ever being arrested compared to an average student. The more closely the peers live, the more likely they will have a partnership on crime.
Jacob, B. A., & Lefgren, L, 2003.	Fixed effects	The aim is to find connection between the school off session and criminal activity.	Jacob & Lefgren (2003) find that school appears to reduce juvenile property crimes by 15 percent but it increases the level of juvenile violent crime by almost 30 percent.

(continues)

TABLE 1 Summary of studies

Carrell, Hoekstra, Kuka, 2018	Fixed effects	Studies the long-term impact of disruptive peers. The idea is to find the impact of disrupted kids in a class on outcome variable like test scores, college enrollment, college graduation, labor force participation and earnings, when controlling for school-by-grades fixed effects, grade-by-year fixed effects and the portion of disruptive peers in class.	Adding one disruptive student to a class of 25 in grades 3 to 5 reduces achievement by 0.014 standard deviation. Results indicate that it is the boys who affect the outcome and especially boys from those families that have not yet reported the domestic violence.
Carrell & Hoekstra, 2010	Fixed effects	Studies the short-term impact on disruptive peers. They use domestic violence as a proxy for disruptive peer and they test the effect of portion of these peers in a class, controlling for school, grade, year and other attributes.	Adding one disruptive peer in a class of 20 students will increase the number of disciplinary incidents by 1.86. Researchers also look the heterogeneity of the outcomes and find that the spillovers vary across gender and family income and are caused primarily by boys.
Angrist & Lang, 2004	IV-method	The strategy is to measure the differences between Metco students in a class compared to a not Metco student in a class when all other background characteristics equals.	The study finds little evidence of Metco students impact on non-Metco classmates. They find some evidence for a negative impact of portion Metco on the test scores of black third graders.

(continues)

TABLE 1 Summary of studies

Damm & Dustmann, 2014	Fixed effects	Investigates the effect of early exposure to neighborhood crime on later criminal behavior of youth. The idea is to measure if the number of criminals in the area had an impact on refugee's criminal activity. They use the quasi-randomization and control other background characteristic.	One standard deviation higher rate of criminals increases the probability of a crime conviction by 4 percent. The results indicate that it is mainly youth violent crime conviction rate that affect individual criminal behavior and it is the share of criminals that has an effect, not the share of criminality.
Bayer, Hjalmarsson, Pozen, 2009	Fixed effects	The idea is to measure peer by exposure to particular characteristic by weighting the average as a number of days the individual spends with each peer. Estimating effect on peer to the recidivism for those who have and have not a prior history of certain crime.	The results show that one standard deviation increase in exposure to peer affect 0.19 on burglary crime which means that the likelihood of recidivism increases from 13.6% to 16.6%. One standard deviation increase on exposure to peers with drug felony history increases the likelihood to recidivate from 28.5% to 31.6%.

4 DATA AND METHODOLOGY

4.1 Data

To implement my empirical analysis I link five different data sets. I use school choice data from statistics of Finland, which includes all students who graduated from secondary school between the years 1991-2007. From this data I exclude those students who did not graduate in that specific year. In the school choice data, there are from 90000 to 140000 observations per year but about 70 % of those applicants are the ones who were graduated in that specific year including also those who graduated in the same year but did not apply to a high school or vocational school. From this data I exclude those students whose class or school information is missing. According to an employee of the statistics of Finland reasons for missing information about school and class can be that the applicant has studied abroad, the school is new and they do not have information about it or information is missing for random reasons. I also drop those observations where the amount of students in school is less than 9 and those who are in a class where amount of students is less than four. This leaves me with 65% to 96% (depending on year) from those individuals who were graduated in the specific year. Data contains about 64000 individuals per year with information of school, class, grades and year of graduation.

I link this data to FLEED (Finnish Longitudinal Employer-Employee Data) in a way that allows me to get individual background information like gender and native language. Data also includes the outcome variables, which are the information about education and employment status after four years of individuals' graduation from secondary school. This information was then linked to a crime data offered by statistics of Finland, allowing me to recognize individual criminal record with different crime types, crime time and sentences. Crime data contains all crimes committed by individuals who were born between the years 1971-1992. Crime information is available from all individuals from school choice data due to the reason that in Finland kids go to school at the age of seven and at the age of 16 they finish secondary school.

Next, I linked this student level and crime data to two different individuals' parents' data offered by statistics of Finland. The other data includes employment and earning information about the individuals' parent and the other data includes all the crimes that individuals' parents have done. Parent crime data does not allow to separate different crime types but it includes information about sentences that allow me to separate serious crimes from other crimes. The information's of parents are from the same year when child graduates from secondary school.

All this data is linked to each other with a unique id code. This data enables me to observe individuals who were in the same school and in the same class connected to their school performance at upper secondary level and school enrollment, graduation and employment four years after finishing the 9th grade with information of all crimes that the young had made in the next eight years after graduation. All this information is linked to individuals' parents which allowed control individuals' background.

Table 2 shows descriptive statistics for the main independent variables and individuals background. I use the word "disruptive peer" to describe those children whose parent has commit any crime. The average amount of disruptive peers in class is 26 percent. The average amount of those peers in a class whose parent has made a serious crime is a lot smaller, only 2 percent. The high portion of disruptive peers in a class is because of the reason that every crime is counted for that measure, including traffic crimes (which are the most common crimes). The portion of disruptive boys is the same 13 percent as the portion of disruptive girls, which should not be too big a surprise especially when the amount of boys and girls is almost the same in this dataset (51% of boys, 49% of girls).

TABLE 2 Descriptive statistics of independent variables.

	Mean	Standard deviation
Male	0.51	0.50
Other language (Not Finnish or Swedish)	0.015	0.51
Disruptive peer	0.26	0.44
Portion of disruptive peers in a class	0.26	0.12
Portion of disruptive peers whose parent has made a serious crime in a class	0.02	0.04
Portion of disruptive peers in a school	0.26	0.07
Portion of disruptive peers whose parent has made a serious crime in a school	0.02	0.02
Portion of disruptive boy peers in a class	0.13	0.09
Portion of disruptive girl peers in a class	0.13	0.09
Portion of disruptive boy peers in a school	0.13	0.05
Portion of disruptive girl peers in a school	0.13	0.04
Amount of students in class	19.60	4.28
Amount of students in 9th grade (per school)	111.15	46.86
Parent's income	45608.18	50812.58
Portion of the Swedish speakers	0.05	0.21
N	1030059	

Table 3 shows as descriptive statistics of dependent variables. Every outcome variable is a dummy, except amount of crimes. The average amount of crimes is 0.62 crimes. The mean for a crime made in eight years after finishing secondary school is 0.12, which would mean that 12 % of the people who were graduated from secondary school committed some crime in the next eight years. The mean for making a crime after two years from graduation is four percent, which is a lot smaller. The average is 0.0048 for those crimes where sentence is prison time, meaning that 0,5 percent of the people who were graduated from secondary school made an very serious crime.

TABLE 3 Descriptive statistics of dependent variables.

	Mean	Standard deviation
Amount of crimes	0.62	5.16
Any crime	0.15	0.36
Crime in 8 years after graduation	0.12	0.32
Crime in 2 years after graduation	0.04	0.21
Drug crime	0.02	0.13
Serious crime	0.005	0.07
Property crime	0.04	0.19
Violent crime	0.04	0.18
Matriculation examination	0.53	0.50
No degree	0.19	0.39
NEET	0.18	0.38
N	1030059	

The average of a matriculation examination is 0.53, meaning that over half of cohort will complete the degree. The amount of people who did not have an upper second level degree after four years from finishing secondary school is 19 percent. This is a bit surprising, but even more surprising is the portion of people who did not have a secondary degree, are not working or in the military service[3] after four years of graduating from secondary school. The portion of these people is 18 percent. This number includes also those who have changed their upper secondary degree study plan (for example changed from high school to vocational school) and for that reason they are not graduated in four years[4].

4.2 School choice in Finland

In Finland students usually go to primary school based in the area they live in. Municipality is responsible for offering free education for every child. Primary school includes grades 1-6 (elementary school) and grades 7-9 (secondary school). Schools offer either one of them or both of them. Municipality decides school boundaries and every child has a right to go to his own local school. Every child has to accomplish education, which starts at the age of seven and ends at the age of 17 or ten years after starting school.

If a child and his parents decide to apply to another school than their local school, they have the right to do so. Child has the right to go to other school than he is ordered if he has a heavy reason. These kinds of reasons can be for example health or language reasons. Schools can take children from another school boundary if there are empty spaces left. Children are accepted by using equal selection criteria like having siblings in a certain school or a distance from

[3] Military service is mandatory for males in Finland.
[4] A normal upper secondary level degree takes three years.

home. Some schools also weight subjects like mathematics, sports or art and take children in by using separate entrance exams.

When a child finishes the 6th grade he moves to the 7th grade and in this point he will move from the elementary school to the secondary school. Children are allowed to hope one or more classmates (depends on school) to their new class, but of course all wishes cannot come true. Schools form the classes independently trying to form classes so that they are balanced between the genders, offering every child an equal studying environment, taking care of child's learning and wellbeing and avoiding segregation. However, the law guides schools in this forming by ordering the basic principles of equal studying environment. Schools can form classes also on the basis of child's optional studies like a language or other optional choices.

4.3 Identification strategy

The two main problems when investigating peer effects are a reflection problem and selection bias. Reflection problem arises, because it is hard to distinguish the effect that a person A has on individual from the effect that person B has on person A. To overcome this reflection problem, I chose to follow a strategy using preexisting measures for peers as a proxy for "quality" of a child. In the earlier literature, similar kind of solutions have been used by many researchers (Deming 2011; Billings et al. 2013; Billings et al 2016; Angrist & Lang, 2004; (Carrell & Hoekstra 2010; Carrell et. al, 2018). However, I find using measures such as race kind of rough and I follow Carrell & Hoekstra (2010), but instead of using domestic violence as proxy of "troubled peers", I use parent's criminality as a measure for "quality" of a child. This option overcomes the reflection problem as long as students' peers do not cause the parents criminality. This seems like a highly reasonable assumption.

When an individual self-selects into a peer group (for example hopes classmates) it is difficult to determine whether the outcome is a causal effect of the peers or the actual reason why the individual joined the group (Hoxby, 2002). Resolving this selection problem, I again follow Carrel & Hoekstra (2010) to exploit the natural variation of cohorts across time within school and class. This can be done by using large panel dataset with a fixed effects models, controlling school-grade-year, class-grade-year and all the necessary background characteristics like gender, race, family income etc. I rely on the natural variation of peers linked to parents who have made a crime within a school level and within a class label level. I do not follow the same individuals in time so I use the year-to-year variation of disruptive peers in a class label. By class label I mean for example class label 9A in a specific school. In this study school-grade specific fixed effects are controlled automatically because data includes only 9th graders[5]. This strategy relies on the assumption that the composition of cohorts remains similar in a school and in a class.

4.4 Fixed effects

Fixed effects model is used when one wants to control an attribute, which differs between individuals or groups, but does not change over the time. The idea is to control unobserved variable, which is time-invariant. In this research I need to use fixed effects, since schools can differ. For example, the criminal rates of the areas where schools are can differ or the composition of students can differ between schools. In my study I use group fixed effects, not individual fixed effects. To deal with the unobserved time-invariant factors, let us write a following equation:

(1) $E(Y_{0it} | A_g , X_{it}, t, d_{it}) = E(Y_{0it} | A_g, X_{it}, t),$

where X_{it} is a vector of observed time-varying covariates, Y_{it} is the outcome variable for individual i on time t and A_g is a vector unobserved but fixed confounders. Variable d_{it} is the variable, which denotes the target of interest (in my case it is portion of disruptive peers). The key to fixed effects estimation is the assumption that the unobserved A_g appears without a time subscript in a linear model for:

(2) $E(Y_{0it} | A_g, X_{it}, t) = a + \mu_t + A_g' \boldsymbol{\gamma} + X_{it}' \beta,$

Assuming that the causal effect of the target of interest is additive and constant:

(3) $E(Y_{1it} |, A_g, X_{it}, t) = E(Y_{0it} | A_g, X_{it}, t) + \rho$

Putting these together, we get:

(4) $E(Y_{it} | A_g, X_{it}, t, d_{it}) = a + \mu_t + \rho d_{it} + A_g' \boldsymbol{\gamma} + X_{it}' \beta,$

where ρ is the causal effect of target of interest. Putting this to another form we get,

(5) $Y_{it} = a_g + \mu_t + \rho d_{it} + X_{it}' \beta + \varepsilon_{it}$, where

(6) $\varepsilon_{it} \equiv Y_{it} - E(Y_{it} |, A_g, X_{it} t)$ and

[5] I observe only the 9th graders so using school-grade fixed effects is the same as using school fixed effects.

(7) $a_i \equiv a + A_g'\boldsymbol{\gamma}$

This is a fixed effects model. In a panel data, causal effect of target of interest on outcome can be estimated by treating a_g , the fixed effect as a parameter to be estimated. The year effect μ_t is also a parameter to be estimated. The unobserved group effects are coefficients in dummies for each group. Treating group effects this way is algebraically the as estimation in deviations from means. The formula can be rewritten,

(8) $Y_{gt} - \bar{Y} = \mu_t - \bar{\mu} \quad + \rho\left(d_{gt} - \bar{d}_g\right) + \left(X_{gt} - \bar{X}_g\right)'\beta + (\mathcal{E}_{gt} - \bar{\mathcal{E}}),$

Now the deviations from means deletes the unobserved group effects. (Angrist & Piscke (2009))

4.5 The model

I start my analysis by estimating the following equations using ordinary least squares:

(9) $y_{ist} = a + b_1 \frac{\sum_{k \neq i} D_{kst}}{n_{st} - 1} + b_2 D_{ist} + b_3 X_{ist} + b_4 G_{st} + \mu_s + \sigma_t + \varepsilon_{ist},$

where y_{ist} is the outcome variable for individual i, in school s, and in year t. Outcome variables of interest are different crimes, graduation from high school, if individual is NEET (not educated, employed, training or in the army) and no degree. $\sum_{k \neq i} R_{kst}/(n_{st} - 1)$ is the proportion of peers in the school cohort of individual whose parent has committed a crime, except individual i itself. μ_s and σ_t are school and year fixed effects. This equation allows me to identify the peer effects within school level but in order to identify the peer effects within class level I use the following equation where I control the class label fixed effects. The next step in my analysis is to estimate the following equation:

(10) $y_{isct} = a + b_1 \frac{\sum_{k \neq i} D_{ksct}}{n_{sct} - 1} + b_2 D_{isct} + b_3 X_{isct} + b_4 C_{sct} + \mu_{sc} + \sigma_t + \varepsilon_{isct},$

where y outcome includes the same target of interest as the previous one. $\frac{\sum_{k \neq i} R_{ksct}}{n_{sct} - 1}$ is the proportion of peers in the class of an individual whose parent has committed a crime, except an individual i itself. In both equations D_{ist} and D_{isct} are dummies which get value one if individual's parent has committed any crime. X_{ist} and X_{isct} are vectors of individual controls. These control variables are parents' income, native language and gender. ε_{ist} and ε_{isct} are error terms. I separate parental income into three different categories: High income, medium income and low income. In the tables the high and medium incomes are compared to the low income, the estimate of a girl is compared to a boy and the estimates of language variables (Swedish and Non-native) are compared to a Finnish language. Equations also include cohort G_{st}/class size C_{sct} control. All standard errors are clustered at a class level or at a school level, because of the potential correlation of those who attend the same class or school.

There is a potential concern when estimating peer effects models (Angrist, 2014). This concern is the mechanical correlation between one's own and peer characteristics when using peer averages as an independent variable. However, I am able to break this concern, because I can clearly separate those who are affecting those who are affected. I test this concern and indeed there is a negative mechanical correlation but its magnitude is really small. Additionally I run regressions where I exclude those students whose parent has made a crime to see whether the results lose their significance and I find that the estimates change slightly but remain statistically significant (see appendix, Table 19 and 20). For that reason I am not worried about the mechanical correlation in this data set.

Despite this, the validity of my research can be threatened if students select into or out of schools, because they know whose parents have committed a crime and they want to avoid those children. My estimates could be biased if parents moved their children to a school from another because of disruptive peers. However, this would seem a very strong response, it is more likely that they complain to a school principle and their children will be just moved to another class. If this is the case, it does not do any harm to my school level estimation, due to the reason I use the variation of disruptive peers within school. However it can do harm to my class level estimation.

Because of potential selection problem, I use class label fixed effects based on the idea that if there is some kind of selection into classes, then we might assume that this selection happens with the same pattern within school. For example if there is a music class in the school and it is the A-grade this year, it is most likely going to be A-grade the next year. However, I note that there is a possibility that the classes do not have the same composition from year to year. If this is true, it will cause damage to the validity of my research. Testing this problem is hard, because there is missing information about additional information of classes in this data set. However, I am able to test this possible selection problem differently by checking the conditional correlations between the portion of disruptive peers and background characteristics. Based on these estimates, I do not find strong evidence of self-selection.

I measure the criminality for every individual after eight years from his or her graduation from secondary school. This is because the school data is from graduate years 1991-2007 and the individuals' crime data is from years 1992-2015 and in order to get a comparable result I choose to follow an individual for eight years after their graduation from the secondary school. Crime data includes all individuals from school data who have committed a crime. I also check the result for two years after their graduation. One outcome variable is

NEET, which gives value 1 if an individual does not have upper secondary level degree, he is not working, or is not in the army after four years of graduating from secondary school. I also use as an outcome variable if he or she does not have upper secondary level degree four years after graduation from secondary school and additionally I check whether the individual has a matriculation examination at the end of year 2015.

I separate different crime types and split them into different groups. The groups are a property crime, violent crime, drug crime and serious crime. Property crime includes crimes like theft, burglary and nuisance. A violent crime includes crimes such as assault, homicide, robbery and sexual offence. Drug crimes include all crimes related to drugs such as possession, buying and selling. Serious crime is a crime where a conviction is unconditional which means that the sentence is to get into a prison. I also use as outcome variable the amount of crimes, which includes every crime that an individual has ever made with equal weight, including traffic crimes. I separate the crimes that parents have committed into two different categories. The first category is any crime, which gets value 1 if an individual's parent has made any crime. The second category is a serious crime, where the variable gets value 1 if an individual's parent has made a crime which sentence is prison time. This enables me to test if there is a stronger peer effect when connecting with peers whose parent has made serious crimes.

5 RESULTS

In my empirical analyses, I focus on a few main results. I examine the impact of a disruptive peer at a class level and at a school level on criminality. I then look the heterogeneous effects of the impact by gender. I analyse the impact of a disruptive peer who is a boy and then the impact of a disruptive peer who is a girl. I divide the data into two parts, one including only boys and the other including only girls. This way I can separate the impact of a disruptive boy on boys and the impact of a disruptive girl on girls. I will also talk about the effects of a disruptive peer on serious crime and the effect of disruptive peer whose parent has made a serious crime.

Additionally I analyse the effects of a disruptive peer on educational outcomes such as the matriculation examination, no degree and on outcome, which describes if a person does not have an upper secondary level degree, a person is not employed and has not served in military.

To analyse the percentage change in a variable of interest I multiply the estimate of portion of disruptive peers by the number, which equals with one additional student (0.05 in a class level) and then count the percentage change from the mean. Since I use this logic to count the effects at class level, I use the same logic to count the effects at school level. I divide the estimates of portion of disruptive peers in school by 20, which equals to 5 per cent increase in the portion of disruptive peers.

5.1 Peer effects on crime

Table 4 shows the result of an effect of disruptive peer to any crime at a school level. Variable any crime gets value 1 if individual has made literally any crime in the next 8 years after finishing secondary school. Results show that there is no statistically significant impact when additional controls are added. In all tables additional controls include gender, native language, the size of a 9th grade (or the size of a class) and parents' income. However, when only a school and year fixed effects are included there is a statistically significant effect in a variable, which measures the portion of disruptive peers in school.

TABLE 4 Effects of Disruptive Peers on criminality (a school level)

	Crime in 8 years	Crime in 8 years	Crime in 8 years	Crime in 8 years
Specification	(1)	(2)	(3)	(4)
Portion of disruptive peers in school	0.247 (0.010)**	0.017 (0.008)*	0.007 (0.007)	0.013 (0.007)
1.Parents' income			-0.051 (0.001)**	-0.040 (0.001)**
2.Parents'income			-0.087 (0.001)**	-0.070 (0.001)**
Number of students at the 9th grade			-0.000 (0.000)**	-0.000 (0.000)**
Girl			-0.145 (0.001)**	-0.146 (0.001)**
2.Language (Swedish)			-0.012 (0.005)*	-0.010 (0.005)*
3.Language (Other than Finnish or Swedish)			0.061 (0.003)**	0.071 (0.003)**
Own parent has commit a crime				0.078 (0.001)**
cons.	0.053 (0.003)**	0.037 (0.008)**	0.192 (0.007)**	0.164 (0.007)**
R^2	0.00	0.01	0.07	0.08
N	1,030,059	1,030,059	1,030,059	1,030,059
Year Fe	Yes	Yes	Yes	Yes
School Fe	No	Yes	Yes	Yes
Additional controls	No	No	Yes	Yes
Mean Y	0.117	0.117	0.117	0.117

Note: **p<0.01,*p<0.05. Each column represents different regression. Robust standard errors in parentheses are clustered at the 9th grade level.

Table 5 shows the same results, but at class level. Now the impact of disruptive peers is statistically significant even, when controlled year, school, class label fixed effects and additional controls. The estimated value of one percentage point increase in the portion of disruptive peers in class is 0.046. This would roughly mean that in a class of 20 people, adding one disruptive peer would equal with 0,23 percentage point increase in estimated probability making any crime. This is approximately 2 per cent increase in the others' probability of making a crime.

TABLE 5 Effects of Disruptive Peers on criminality (a class level)

	Crime in 8 years	Crime in 8 years	Crime in 8 years	Crime in 8 years	Crime in 8 years
Specification	(1)	(2)	(3)	(4)	(5)
Portion of disruptive peers in class	0.178 (0.004)**	0.127 (0.004)**	0.089 (0.004)**	0.042 (0.003)**	0.046 (0.003)**
1.Parents' income			-0.049 (0.001)**	-0.047 (0.001)**	-0.037 (0.001)**
2.Parents' income			-0.084 (0.001)**	-0.080 (0.001)**	-0.064 (0.001)**
Number of students at a class			-0.005 (0.000)**	-0.002 (0.000)**	-0.002 (0.000)**
Girl			-0.144 (0.001)**	-0.142 (0.001)**	-0.142 (0.001)**
2.Language (Swedish)			-0.014 (0.005)**	-0.013 (0.005)**	-0.011 (0.005)*
3.Language (Other than Finnish or Swedish)			0.058 (0.003)**	0.059	0.069
			(0.003)**	(0.003)**	(0.003)**
Own parent has commit a crime					0.075 (0.001)**
cons.	0.069 (0.002)**	0.009 (0.008)	0.244 (0.007)**	0.245 (0.003)**	0.218 (0.003)**
R^2	0.00	0.01	0.08	0.09	0.10
N	1,030,059	1,030,059	1,030,059	1,030,059	1,030,059
Year Fe	Yes	Yes	Yes	Yes	Yes
School Fe	No	Yes	Yes	-	-
Class labelFe	No	No	No	Yes	Yes
Additional controls	No	No	Yes	Yes	Yes
Mean Y	0.117	0.117	0.117	0.117	0.117

Note: **p<0.01,*p<0.05. Each column represents different regression. Robust standard errors in parentheses are clustered at the class level.

When looking at the effects (See appendix Table 15) of a disruptive peer whose parent has made a serious crime, the estimated value is 0.061. This would equal with 0,03 percentage point increase in probability making a crime, which is approximately 3 percentage increase in a probability making a crime in a class of 20 people. Again, there is no impact when looking at the effects at a school level (See Appendix Table 15).

Interestingly, the peer effect of making a serious crime gets statistically significant value. Table 14 (Appendix) shows the effect of disruptive peers to serious crime. The estimate gets value of 0.006, which can be expressed as a 0,03 percentage point increase. The mean for making a serious crime is half a per cent, so the 0,03 percentage point increase would be approximately 6 per cent increase in the others' probability of making a serious crime. I note that the mean for making a serious crime is very small. When looking at these same results in at a school level from table 13 (Appendix), it can be seen that there is no statistically significant effect.

5.2 Effects by gender

Table 6 shows the effects by gender at a class level. When looking at the effect of a disruptive boy peer, table 6 shows that the estimated value is 0.06. This is approximately 2,5 per cent increase in a probability of making any crime in a class of 20 people. The effect of a disruptive girl peer is considerably smaller, only about one per cent. The interesting finding of this research is that there are significant differences when looking at the gender-to-gender effects. The estimated effect of disruptive boy peer on a boy is approximately 2,5%, whereas the effect of a disruptive girl peer on a girl is approximately 1,5%. The effect of a boy peer on a girl is as much as the effect of a boy peer on a boy, but the effect of a girl peer on a boy is approximately 1,1 %. These results imply that it is the disruptive boys who have the stronger effect on others[6]. There were no significant results found at a school level.

[6] I note that splitting the data to only male and only female means that I basically take interaction term between gender and every right hand side variable. I also test gender effects by using interaction term with portion of disruptive peers and gender (see Appendix Table 21). I find that disruptive boy peer has stronger effect on every outcome and that the effect of a disruptive boy peer and a disruptive girl peer on female is close to zero.

TABLE 6 Effects of Disruptive Peers on crime by gender (a class level)

	All	Male	Female
Specification	(1)	(2)	(3)
Fraction of disruptive boy peers	0.064 (0.005)**	0.096 (0.007)**	0.025 (0.004)**
Fraction of disruptive girl peers	0.026 (0.004)**	0.035 (0.007)**	0.014 (0.004)**
N	1,030,059	523,243	506,816
Year Fe	Yes	Yes	Yes
Class label Fe	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes
Mean Y	0.117	.189	0.044

Note: **p<0.01,*p<0.05. Each column represents different regression. Robust standard errors in parentheses are clustered at the class level. Additional controls include gender, language, the amount of students in a class, own parents' criminality and parents' income.

5.3 Educational outcomes

Next I will analyse educational outcomes. These results are shown in Table 7 and 8. Table 7 shows the results at school level. There are no significant effects on NEET and matriculation examination, but there is a little effect on the no degree outcome. 5 percentage point increase in a portion of disruptive peers at grade will increase the others' probability of not getting any degree after four years finishing the secondary school by 1,3 per cent.

TABLE 7 Effects of Disruptive Peers on education (a school level)

	NEET	No degree	Matriculation exam.
Specification	(1)	(2)	(3)
Portion of disruptive peers in school	0.006 (0.009)	0.052 (0.010)**	-0.031 (0.011)**
1.Parents' income	-0.060 (0.001)**	-0.080 (0.001)**	0.132 (0.001)**
2.Parents' income	-0.109 (0.001)**	-0.151 (0.001)**	0.335 (0.002)**
Number of students at the 9th grade	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Own parent has commit a crime	0.042 (0.001)**	0.097 (0.001)**	-0.110 (0.001)**
Girl	-0.029 (0.001)**	-0.040 (0.001)**	0.178 (0.001)**
2.Language (Swedish)	-0.011 (0.005)*	-0.013 (0.006)*	-0.002 (0.007)
3.Language (Other than Finnish or Swedish)	0.028 (0.004)**	0.114 (0.004)**	-0.036 (0.004)**
cons.	0.320 (0.004)**	0.232 (0.004)**	0.333 (0.005)**
R^2	0.05	0.06	0.14
N	1,030,059	1,030,059	1,030,059
Year Fe	Yes	Yes	Yes
School Fe	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes
Mean Y	0.18	0.19	0.53

Note: **p<0.01,*p<0.05. Each column represents different regression. Robust standard errors in parentheses are clustered at the class level.

Table 8 shows that disruptive peers have an effect on others' educational outcomes when looking at the class level. Columns (1), (2) show the effect on outcome NEET (not in employment, education or training) and no degree. The estimated effect of a disruptive peer for NEET is 0,2 percentage point increase, meaning 1,1 per cent increase in a probability of becoming NEET. The estimated effect for no degree is 0,37 percentage point increase, which equals with 2 per cent increase in others' probability for not getting any secondary degree. Column (3) shows the estimates for matriculation examination. The estimate for matriculation examination implies that adding one disruptive peer into a class of 20 people decreases the probability of getting a matriculation examination by 0,61 percentage point, meaning 1,1 per cent decrease in others' probability of getting a matriculation examination.

TABLE 8 Effects of Disruptive Peers on education (a class level)

	NEET	No degree	Matriculation exam.
Specification	(1)	(2)	(3)
Portion of disruptive peers in class	0.040 (0.004)**	0.073 (0.004)**	-0.123 (0.005)**
1.Parents' income	-0.058 (0.001)**	-0.076 (0.001)**	0.127 (0.001)**
2.Parents' income	-0.104 (0.001)**	-0.142 (0.001)**	0.322 (0.001)**
Number of students at a class	-0.002 (0.000)**	-0.003 (0.000)**	0.005 (0.000)**
Own parent has commit a crime	0.040 (0.001)**	0.093 (0.001)**	-0.106 (0.001)**
Girl	-0.027 (0.001)**	-0.036 (0.001)**	0.173 (0.001)**
2.Language (Swedish)	-0.012 (0.005)*	-0.012 (0.006)*	-0.001 (0.007)
3.Language (Other than Finnish or Swedish)	0.024 (0.004)**	0.106 (0.004)**	-0.026 (0.004)**
cons.	0.344 (0.003)**	0.277 (0.004)**	0.284 (0.005)**
R^2	0.06	0.08	0.16
N	1,030,059	1,030,059	1,030,059
Year Fe	Yes	Yes	Yes
Class label Fe	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes
Mean Y	0.18	0.19	0.53

Note: **p<0.01,*p<0.05. Each column represents different regression. Robust standard errors in parentheses are clustered at the class level.

I find a similar kind of pattern when looking at the gender effects on educational outcomes. On every outcome, a disruptive boy affects more than a disruptive girl. These results can be seen from Table 16 (Appendix). Table 17 and 18 (Appendix) shows the gender-to-gender effects[7]. A disruptive boy peer affects more on a boy than a disruptive girl does. Similarly a disruptive boy peer also affects more on a girl than a disruptive girl does. These results have the same implication as with crime outcomes. It seems that it is the disruptive boy who has a stronger effect on outcomes.

[7] I also test gender effects using interaction term (see Appendix Table 21). Disruptive boys affect more than disruptive girls do on every outcome except on females' matriculation examination.

5.4 Robustness check

I use two different tests to see if my results hold. Firstly, I use different outcome variables to see if the results change. I use variables such as crime amount, property crime, violent crime and crime after two years, which describes the immediate effect of disruptive peers. Secondly, I include school-year fixed effects, which should capture any common shock that could drive my results. I do this because there is a chance that some schools and neighbourhoods might worsen over time and this would possibly affect the criminality of parents and young people and also to other outcomes of young people.

TABLE 9 Effects of Disruptive Peers on different crimes (a class level)

	Crime amount	Crime in 2 years	Property crime	Violent crime
Specification	(1)	(2)	(3)	(4)
Portion of disruptive peers in class	0.556 (0.076)**	0.028 (0.002)**	0.027 (0.002)**	0.023 (0.002)**
1.Parents' income	-0.382 (0.013)**	-0.017 (0.001)**	-0.021 (0.000)**	-0.015 (0.000)**
2.Parents' income	-0.534 (0.014)**	-0.028 (0.001)**	-0.034 (0.001)**	-0.026 (0.001)**
Number of students at a class	-0.034 (0.002)**	-0.002 (0.000)**	-0.001 (0.000)**	-0.001 (0.000)**
Own parent has commit a crime	0.652 (0.015)**	0.035 (0.001)**	0.035 (0.001)**	0.031 (0.000)**
Girl	-0.865 (0.010)**	-0.058 (0.000)**	-0.046 (0.000)**	-0.044 (0.000)**
2.Language (Swedish)	-0.103 (0.071)	-0.000 (0.003)	-0.001 (0.003)	-0.004 (0.003)
3.Language (Other than Finnish or Swedish)	0.233 (0.063)**	0.032 (0.002)**	0.023 (0.002)**	0.044 (0.002)**
cons.	1.686 (0.055)**	0.097 (0.002)**	0.091 (0.002)**	0.071 (0.002)**
R^2	0.07	0.07	0.07	0.06
N	1,030,059	1,030,059	1,030,059	1,030,059
Year Fe	Yes	Yes	Yes	Yes
Class label Fe	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes
Mean Y	0.62	0.044	0.038	0.035

Note: **p<0.01,*p<0.05. Each column represents different regression. Robust standard errors in parentheses are clustered at the class level.

Different crime type outcomes can be seen in table 9. The column (1) shows that adding one disruptive peer in a class of 20 increases the amount of crimes by 2,78. The column (2) shows the variable which measures any crime made after 2 years of graduation. This is an interesting variable, because it shows the immediate effect of a disruptive peer. The estimated effect for this is approximately 3 % increase in probability of making any crime. Column (3) and (4) shows the estimates for a property crime and for a violent crime. The estimates implicate that there is a 0,13 and 0,12 percentage point increase, meaning 3,5% percentage increase in a probability of making property crime and 3,2% increase of making a violent crime. All these results are at a class-level.

In table 10 I include school-year fixed effects to see whether common shocks are driving my results on main outcome variables. In the table can be seen the comparison between the coefficients of portion of disruptive peers at a class in regression where school-year fixed effects is included and the regression where it is not included. For every outcome the estimated value is almost the same and every coefficient is statistically significant. There is also another observation, which can be made based on table 10. If the estimate would be higher in columns where the school-year fixed effects are controlled, it would indicate that disruptive peers are placed into the same class (since the variation of disruptive peers in class comes within school-year). However, this is not the case here and at least based on this test I do not find evidence of self-selection.

TABLE 10 Effects of Disruptive Peers (a school level)

	Crime in 8 years	Crime in 8 years	Serious Crime	Serious Crime	NEET	NEET	No degree	No degree	Matriculation exam.	Matriculation exam.
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Portion of disruptive peers in class	0.074 (0.004)**	0.089 (0.004)**	0.012 (0.001)**	0.013 (0.001)**	0.060 (0.004)**	0.060 (0.004)**	0.103 (0.005)**	0.10 (.005)**	-0.162 (0.006)**	-0.162 (0.006)**
N	1,030,059	1,030,059	1,030,059	1,030,059	1,030,059	1,030,059	1,030,059	1,030,059	1,030,059	1,030,059
Year Fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School Fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-year Fe	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.09	0.08	0.04	0.02	0.06	0.06	0.07	0.07	0.15	0.15
Mean Y	0.12	0.12	0.005	0.005	0.18	0.18	0.19	0.19	0.53	0.53

Note: **p<0.01,*p<0.05. Each column represents different regression. Robust standard errors in parentheses are clustered at the class level. Additional controls include gender, language, amount of students in class/9th grade, own parents' criminality and parents' income.

These results are important, because the variable any crime includes also crimes such as traffic crimes, which someone could consider not being a “real crime”. My results seem to be robust when looking at the different crime types and this indicates that it is not only the probability of making any crime that is being affected by disruptive peers. Results seem to be also robust when adding a school-year fixed effect, which indicates that my results are not driven by common shocks. This should not be so surprising giving the fact that my data includes the years between 1991-2007 and it was highly unlike that my results are affected by common shocks in the first place.

5.5 Falsification test

There is a possibility that students self-select into or out of school and classes. My strategy relies on the assumption that there might be some kind of selection into schools and classes but their composition stays unchanged in time and there are no such changes that my control variables could not capture. My estimates could be biased if for some reason my assumption would not hold. I follow Carrell & Hoekstra (2010) and test this assumption by examining if there is a conditional correlation between the portion of disruptive peers in school/class and students’ own exogenous characteristics[8]. These tests are shown in Table 11 and 12. Table 11 shows this test at school level. In the first and second column I test whether the portion of disruptive peer is correlated with gender. The test shows that there is no correlation between the gender and the portion of disruptive peers and also that there is no correlation between the gender and the portion of disruptive peers whose parent have committed a serious crime. Column 3 gives the correlation of person who is not native to the portion of disruptive peers and portion of disruptive peers whose parent has committed a serious crime. These variables are clearly correlated. Column 4 and 5 shows that the portion of disruptive peers have a small correlation between parents’ income and size of 9th grade.

[8] From tables 11 and 12 I exclude those children whose parent have committed a crime, because I want to see if there is a connection between the portion of disruptive peers and other students’ own characteristics.

TABLE 11 Falsification test (a school level).

	Male	Female	Immigrant	Parents' income	Size of 9th grade
Specification	(1)	(2)	(3)	(4)	(5)
Panel A					
Portion of disruptive peers in School	0.021 (0.013)	-0.021 (0.013)	0.031 (0.005)**	-5,298.641 (1,580.535)**	-13.978 (3.373)**
Panel B					
Portion of DV in school whose parent has made a serious crime	-0.022 (0.040)	0.022 (0.040)	0.073 (0.016)**	-14,872.910 (3,201.563)**	-21.081 (10.175)*
N	764,182	764,182	764,182	764,182	764,182
Year Fe	Yes	Yes	Yes	Yes	Yes
School Fe	Yes	Yes	Yes	Yes	Yes
Mean Y	0.51	0.49	0.015	47560	111

Note: **p<0.01,*p<0.05. Each estimate represents different regression. Robust standard errors in parentheses are clustered at the 9th grade level.

Table 12 shows the conditional correlation between the portion of disruptive peers and students' exogenous characteristics at a class level. All variables have statistically significant value. Despite the fact that variables have statistically significant value, the values are small in columns 1 and 2. I note that my sample size is very high (compared for example to Carrell & Hoekstra (2010)) and it is more likely to have statistically significant values with a great sample size. From column 3 it can be seen that not native language is clearly correlated with the portion of disruptive peers. Columns 4 and 5 give the estimated values to parents' income and class size. Parents' income and portion of disruptive peers whose parent has committed a serious crime seems to have a strong connection. Other connections between variables in column 5 and 6 are less than 1 per cent.

TABLE 12 Falsification test (a class level)

	Male	Female	Immigrant	Parents' income	Class size
Specification	(1)	(2)	(3)	(4)	(5)
Panel A					
Portion of disruptive peers in class	0.022 (0.006)**	-0.022 (0.006)**	0.012 (0.002)**	-5,118.266 (572.434)**	-1.402 (0.124)**
Panel B					
Portion of DV in class whose parent has commit a serious crime	0.046 (0.017)**	-0.046 (0.017)**	0.026 (0.006)**	-12,648.345 (1,298.254)**	-2.986 (0.382)**
N	764,182	764,182	764,182	764,182	764,182
Year Fe	Yes	Yes	Yes	Yes	Yes
Class label Fe	Yes	Yes	Yes	Yes	Yes
Mean Y	0.51	0.49	0.015	47560	20

Note: **p<0.01,*p<0.05. Each estimate represents different regression. Robust standard errors in parentheses are clustered at the class level.

The results shown in table 11 and 12 indicate that there is a possibility that the composition of the schools and classes might not be constant over time, at least regarding of these variables, which are tested. Also there might be some attributes, which changes over time within class label and I do not observe them. Clear correlation was found with variable, which describes a person who is not a native speaker. It seems that there could be selection regarding of this variable. Despite this, I am not worried about the fact that this correlation would drive or do any harm to my results, because the portion of the non-native speakers is only 1.5% in my sample. I also remind that even though the estimates in the tables seem remarkable they cannot be interpreted straightly due to the measurement of the portion of disruptive peers variable (it is measured between 0 and 1).

6 DISCUSSION

There are two main findings in this research, which can be seen in the previous chapter. Firstly, it seems that if there is a peer effect at schools it mostly appears at the class level. Almost in all tables it can be seen that there are no peer effects at the school level. Only in a variable no degree it seems to have a small effect on school level. Even though there is a statistically significant effect in some other cases the effects are so small that they can be considered as a zero effect. Unlike at school level, peer effects at class level can be found in every outcome. The second main finding of this research is that the effects vary by gender. In every outcome a disruptive boy peer has more effect than a disruptive girl peer does. The results raise the following question: How do peers affect on individual's educational and criminal outcomes?

There are different explanations why the effects are stronger at a class level than a school level. One obvious explanation could be that the students spend more time with their classmates than with their schoolmates. Classmates have more time to affect their peers in many different ways. According to the Bad apple model, there are many potential ways how a peer can affect education outcomes in a classroom but it is hard to think about the mechanisms at a school level. The same explanation could explain the results of crime outcomes, peers who are in the same class have more time to impact others. Another possible reason for this stronger effect at a class level is that there is endogeneity, because classes are not randomized. I note that I tested this selection problem with different exogenous background variables and I did not found clear evidence about it, but there is some missing information that I cannot control, such as optional study choices and quality of teacher, which can affect to class composition.

There are generally two different ways how peers might affect other students' educational outcomes. They can either disrupt other students or other students have less students to learn from, since from table 8 it can be seen that students who are determined as disruptive peers have on average worse educational outcomes. Similar kind of findings has been made by Carrell & Hoeksta (2010). Carrel et al. (2018) suggest that disruptive peers affect non-cognitive skills rather than cognitive skills, since they find that disruptive peers affect wages and educational outcomes. It is more reasonable to think that peers in general affect more to non-cognitive skills like social-skills than cognitive skills such as a memory. Since I do not have data from the infractions in a class it is hard to say, which one of the mechanisms dominates when thinking about the effect on educational outcomes.

Based on this research it is hard to point the exact mechanism how the peers affect young people's criminality. However, there are two different results that I can utilize to reason this question. The first one is the fact that the effect is stronger at a class level than it is at a school level. This would indicate that the effect is stronger when a student associates with peers more frequently, closer and spends more time with them. Another result, which can be used to reasoning, is the result in the table 9 column 2. That variable measures if a person has committed a crime two years after finishing secondary school. When comparing the size of the effect to the effect peers have on the probability of making a crime after 8 years of graduation it can be seen that it is stronger. The effect on committing a crime after two years is three per cent when the effect on committing a crime after 8 years is two per cent. This would indicate again that the time and frequency affects how strongly the portion of disruptive peers affects criminality. Both of these results are in line with the differential association theory. In addition, it can be clearly seen from table 4 and 5 that disruptive peer himself has a significantly higher probability to commit a crime. Due to that fact, it seems that the mechanism goes through the so called "learning channel": Disruptive peers offer skills and knowledge, which are favourable to criminality.

The question that rises from the second main finding is: Why do the boys affect more than girls do? One quite clear mechanism could be that boys simply disrupt more in the classroom than girls do (Carrell & Hoekstra, 2010 found that boys commit 3 times more infractions than girls do). I am not able to strictly measure the behaviour in a class but for example the average of crime variable is a lot higher for boys than it is for girls (0.19 and 0.04). It can also be that disruptive boys feel that they get a seal of approval from others if they act like a "bad boy". This would encourage them to do things that are related to being a "bad boy", such as disrupting the teaching, not doing their homework, committing and talking about small crimes. Girls might not have this kind of feeling that they need to behave badly in order to get approval or it might even be that other students do not feel that it is cool if girl behaves badly.

One potential explanation for the gender differences is that boys' bad behaviour is tolerated more than girls' bad behaviour. For example if a teacher has a strong "boys will be boys" way of thinking it can be that a teacher tolerates more boys' disruptive behaviour. It is possible that the teacher intervenes more easily in girls' disruptive behaviour, which signals to other girls that bad behaviour is not tolerated.

Since there are the same amount of disruptive boy peers and disruptive girl peers in the data and their "quality" is measured by their parents' criminality it is only natural to think that boys and girls react differently to their home environment. Bertrand and Pan (2013) find that boys who were raised by a single mother had a higher risk to behavioural problems than girls who were raised by a single mother. If the same were true with the boys whose parents have a criminal background it would give a reasonable explanation for my findings. This would indicate that boys are more affected by their background or at least they are more sensitive to behave like it.

My results are in line with the previous research. I find that disruptive peers in a class have a negative impact on others' criminal and educational outcomes. Carrell & Hoekstra (2010) found a negative impact of disruptive peers on educational outcomes. They estimate that adding one disruptive peer in a class of 20 people decreases the test score result by 0.67 percentage points whereas my estimate for matriculation examination is -0.75 percentage points. They also find that disruptive boys have a stronger effect but their differences are stronger than mine are. For example they find that adding one disruptive boy peer in a class of 20 decreases boys' test scores by 2 percentage points, whereas my estimate for disruptive boy peer on boys matriculation examination is only -0,8 percentage points (see Appendix table 17). Billings et al. (2013) estimate that 10 per cent increase in the share of minorities decreased high school test scores by 0.014 standard deviation. Carrell et. al (2018) find that adding one disruptive peer into a class of 25 reduces the probability to get a college degree by 2.2 percentage points.

Billings et al (2013) estimate that 10-percentage point increase in minority assigned to school increases the probability of ever being arrested by 1.5 percentage points. I do not find this similar kind of result at school level but I do find that 10-percentage point increase of disruptive peers in class leads to 0.5 percentage point increase in committing a crime. Adding 8.3 students (one standard deviation) into the same school (same grade-grade-race) increases the probability to ever being arrested by 3.9 percentage point, equalling with 23% increase compared to an average student (Billings et al, 2013). My estimate for parallel situation is 1.9 percentage point increase in a probability of committing a crime, equalling with 16% increase compared to an average student.

7 CONCLUSION

In this paper, I studied the peer effects in schools and classrooms by using the school choice dataset from Finland matched with different datasets, which provides detailed criminal, educational and other relevant information about students and their parents. In order to overcome the well-known problems in peer effects literature I used idiosyncratic year-to-year variation of portion of students whose parents have committed a crime within school and class label, providing me an opportunity to make reliable estimates. I included year, school and class label fixed effects in order to distinguish peer effects from confounding factors. I showed that including own characteristics information do not erase the significance of my results at a class level. I studied peer effects on criminality and education.

There are two important results in this paper. The first one is that adding one child who is determined as a “disruptive peer” in a class of 20 people increases the other students’ probability to commit a crime by 2 percent, decreases the probability to get a matriculation examination by 2 per cent and increases the probability of not getting any degree after secondary school by 1,1 per cent. The second one is that peer effects vary by gender and it is the boys who have more effect on their peers than girls have. I find that these peer effects are statistically significant at a class level but not at a school level. My results are based on the assumptions that there are no such changes in the composition of schools and classes what my control variables could not capture.

To ensure that my results are valid I provided several different tests. I tested the correlation of the portion of disruptive peers between students’ own exogenous characteristics to see whether my results are biased because of the selection problem. I found little evidence of self-selection. I also test whether my results hold with different crime outcome variables to see if the disruptive peers have effect on not only to any crime but also on more serious crimes and to different crime types. I also tested that my results are not harmed because of the measurement type and common shocks and I found that my results are robust.

The main implication of this paper is that schools should think carefully how they allocate troubled children into classes. Due to the reason that there are peers who have negative spillovers to others and that these spillovers get stronger when more troubled peers are added into the same class, schools should think carefully about the placement of potentially disruptive children, especially when they are boys. However, schools have budget restrictions and it is most likely that schools must put some of the disruptive children into the same class. Schools could try to soften these peer effects with different kinds of methods. For example schools could place a highly qualified teacher into the class where they expect or observe to be a large portion of disruptive peers.

Long-term impacts of peers remain unclear and especially the long term effect of labour market outcomes would provide important research target for the future. Another important future research target would be the exact mechanisms of peer effects in the classroom, which unfortunately stays unclear in this paper. Despite that, this paper provides unique information of peer effects in classroom and is important addition to the earlier literature, providing relevant information from a country, which is considered to be one of the most equal one.

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APPENDIX

TABLE 13 Effects of Disruptive Peers on serious crime (a school level)

	Serious Crime	Serious Crime	Serious Crime	Serious Crime
Specification	(1)	(2)	(3)	(4)
Portion of disruptive peers in School	0.041 (0.003)**	0.001 (0.002)	-0.000 (0.002)	0.000 (0.002)
1.Parents' income			-0.005 (0.000)**	-0.004 (0.000)**
2.Parents' income			-0.007 (0.000)**	-0.006 (0.000)**
Number of students at the 9th grade			-0.000 (0.000)	-0.000 (0.000)
Girl			-0.008 (0.000)**	-0.008 (0.000)**
2.Language (Swedish)			-0.001 (0.001)	-0.001 (0.001)
3.Language (Other than Finnish or Swedish)			0.004 (0.001)**	0.005 (0.001)**
Own parent has commit a crime				0.006 (0.000)**
cons.	-0.004 (0.001)**	0.003 (0.001)*	0.013 (0.001)**	0.011 (0.001)**
R^2	0.00	0.01	0.02	0.02
N	1,030,059	1,030,059	1,030,059	1,030,059
Year Fe	Yes	Yes	Yes	Yes
School Fe	No	Yes	Yes	Yes
Additional controls	No	No	Yes	Yes
Mean Y	0.005	0.005	0.005	0.005

Note: **p<0.01,*p<0.05. Each column represents different regression. Robust standard errors in parentheses are clustered at the 9th grade level.

TABLE 14 Effects of Disruptive Peers on serious crime (a class level)

	Serious Crime	Serious Crime	Serious Crime	Serious Crime	Serious Crime
Specification	(1)	(2)	(3)	(4)	(5)
Portion of disruptive peers in a class	0.027 (0.001)**	0.017 (0.001)**	0.013 (0.001)**	0.006 (0.001)**	0.006 (0.001)**
1.Parents' income			-0.005 (0.000)**	-0.005 (0.000)**	-0.004 (0.000)**
2.Parents' income			-0.006 (0.000)**	-0.006 (0.000)**	-0.005 (0.000)**
Number of students at a class			-0.001 (0.000)**	-0.000 (0.000)**	-0.000 (0.000)**
Girl			-0.008 (0.000)**	-0.008 (0.000)**	-0.008 (0.000)**
2.Language (Swedish)			-0.002 (0.001)	-0.001 (0.001)	-0.001 (0.001)
3.Language (Other than Finnish or Swedish)			0.004 (0.001)**	0.004 (0.001)**	0.004 (0.001)**
Own parent has commit a crime					0.006 (0.000)**
cons.	-0.000 (0.000)	-0.001 (0.001)	0.023 (0.001)**	0.018 (0.001)**	0.016 (0.001)**
R^2	0.00	0.02	0.02	0.04	0.04
N	1,030,059	1,030,059	1,030,059	1,030,059	1,030,059
Year Fe	Yes	Yes	Yes	Yes	Yes
School Fe	No	Yes	Yes	-	-
Class label Fe	No	No	No	Yes	Yes
Additional controls	No	No	Yes	Yes	Yes
Mean Y	0.005	0.005	0.005	0.005	0.005

Note: **p<0.01,*p<0.05. Each column represents different regression. Robust standard errors in parentheses are clustered at the class level.

TABLE 15 Effects of Disruptive Peers by type of parent.

	Crime in 8 years		Serious Crime
Portion of DP in school whose parent has made a serious crime	0.002 (0.023)	Portion of DP in school whose parent has made a crime	0.000 (0.002)
Portion of DP in class whose parent has made a serious crime	0.061 (0.011)**	Portion of DP in class whose parent has made a crime	0.006 (0.001)**
		Portion of DP in school whose parent has made a serious crime	-0.002 (0.008)
		Portion of DP in class whose parent has made a serious crime	0.007 (0.004)*
N	1,030,059	*N*	1,030,059
Year Fe	Yes	Year Fe	Yes
School Fe(1.st row)	Yes	School Fe(1.st row)	Yes
Class label Fe (2.nd row)	Yes	Class label Fe (2.nd row)	Yes
Additional controls	Yes	Additional controls	Yes
Mean Y	0.117	Mean Y	0.005

Note: **p<0.01,*p<0.05. Each estimate represents different regression. Robust standard errors in parentheses are clustered at the class level. Additional controls include gender, language, the amount of students in a class/ 9th grade, own parents' criminality and parents' income.

TABLE 16 Effects of Disruptive Peers on educational outcomes by gender (a class level)

	NEET	No degree	Matriculation exam.
Specification	(1)	(2)	(3)
Fraction of disruptive boy peers	0.051 (0.005)**	0.096 (0.006)**	-0.151 (0.007)**
Fraction of disruptive girl peers	0.027 (0.005)**	0.047 (0.005)**	-0.094 (0.007)**
N	1,030,059	1,030,059	1,030,059
Year Fe	Yes	Yes	Yes
Class label Fe	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes
Mean Y	0.18	0.19	0.53

Note: **p<0.01,*p<0.05. Each column represents different regression. Robust standard errors in parentheses are clustered at the class level. Additional controls include gender, language, the amount of students in a class, own parents' criminality and parents' income.

TABLE 17 Effects of Disruptive Peers on boys educational outcomes (a class level)

	NEET	No degree	Matriculation exam.
Specification	(1)	(2)	(3)
Fraction of disruptive boy peers	0.061 (0.007)**	0.103 (0.008)**	-0.162 (0.009)**
Fraction of disruptive girl peers	0.033 (0.007)**	0.045 (0.007)**	-0.088 (0.009)**
N	523,243	523,243	523,243
Year Fe	Yes	Yes	Yes
Class label Fe	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes
Mean Y	0.19	0.21	0.44

Note: **p<0.01,*p<0.05. Each column represents different regression. Robust standard errors in parentheses are clustered at the class level. Additional controls include gender, language, the amount of students in a class, own parents' criminality and parents' income.

TABLE 18 Effects of Disruptive Peers on girls educational outcomes (a class level)

	NEET	No degree	Matriculation exam.
Specification	(1)	(2)	(3)
Fraction of disruptive boy peers	0.040 (0.007)**	0.079 (0.007)**	-0.141 (0.009)**
Fraction of disruptive girl peers	0.017 (0.007)	0.049 (0.007)**	-0.093 (0.009)**
N	506,816	506,816	506,816
Year Fe	Yes	Yes	Yes
Class label Fe	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes
Mean Y	0.16	0.17	0.62

Note: **p<0.01,*p<0.05. Each column represents different regression. Robust standard errors in parentheses are clustered at the class level. Additional controls include gender, language, the amount of students in a class, own parents' criminality and parents' income.

TABLE 19 Effects of Disruptive Peers at a class (DP excluded)

	Crime in 8 years	Serious Crime	NEET	No degree	Matriculation exam.
Specification	(1)	(2)	(3)	(4)	(5)
Portion of disruptive peers in class	0.038	0.004	0.032	0.063	-0.118
	(0.003)**	(0.001)**	(0.004)**	(0.004)**	(0.006)**
1bn.parents' income	-0.027	-0.002	-0.052	-0.062	0.122
	(0.001)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**
2.parents' income	-0.051	-0.003	-0.096	-0.122	0.314
	(0.001)**	(0.000)**	(0.001)**	(0.001)**	(0.002)**
Number of students at a class	-0.002	-0.000	-0.002	-0.003	0.004
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**
Girl	-0.121	-0.005	-0.028	-0.035	0.177
	(0.001)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**
2.Language (Swedish)	-0.008	-0.000	-0.007	-0.011	0.008
	(0.005)	(0.001)	(0.006)	(0.007)	(0.008)
3.Language (Other than Finnish or Swedish)	0.077	0.006	0.030	0.127	-0.041
	(0.004)**	(0.001)**	(0.004)**	(0.005)**	(0.005)**
cons.	0.192	0.010	0.333	0.258	0.285
	(0.003)**	(0.001)**	(0.004)**	(0.004)**	(0.005)**
R^2	0.07	0.04	0.05	0.06	0.14
N	764,182	764,182	764,182	764,182	764,182
Year Fe	Yes	Yes	Yes	Yes	Yes
Class label Fe	Yes	Yes	Yes	Yes	Yes
Mean Y	0.09	0.003	0.16	0.16	0.57

Note: **p<0.01,*p<0.05. Each column represents different regression. Robust standard errors in parentheses are clustered at the class level.

TABLE 20 Effects of Disruptive Peers at a school (DP excluded)

	Crime in 8 years	Serious Crime	NEET	No degree	Matriculation exam.
Specification	(1)	(2)	(3)	(4)	(5)
Portion of disruptive peers in School	0.007 (0.008)	-0.000 (0.001)	0.004 (0.010)	0.047 (0.010)**	-0.028 (0.012)*
1bn.parents' income	-0.029 (0.001)**	-0.002 (0.000)**	-0.053 (0.001)**	-0.065 (0.001)**	0.126 (0.001)**
2.parents' income	-0.055 (0.001)**	-0.003 (0.000)**	-0.100 (0.001)**	-0.128 (0.001)**	0.326 (0.002)**
Number of students at a class	-0.000 (0.000)*	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Girl	-0.123 (0.001)**	-0.005 (0.000)**	-0.030 (0.001)**	-0.037 (0.001)**	0.181 (0.001)**
2.Language (Swedish)	-0.009 (0.005)	-0.000 (0.001)	-0.008 (0.006)	-0.012 (0.007)	0.008 (0.008)
3.Language (Other than Finnish or Swedish)	0.081 (0.004)**	0.007 (0.001)**	0.034 (0.004)**	0.137 (0.005)**	-0.054 (0.005)**
cons.	0.178 (0.004)**	0.009 (0.001)**	0.309 (0.005)**	0.220 (0.005)**	0.335 (0.006)**
R^2	0.06	0.01	0.04	0.04	0.12
N	764,182	764,182	764,182	764,182	764,182
Year Fe	Yes	Yes	Yes	Yes	Yes
School Fe	Yes	Yes	Yes	Yes	Yes
Mean Y	0.09	0.003	0.16	0.16	0.57

Note: **p<0.01,*p<0.05. Each column represents different regression. Robust standard errors in parentheses are clustered at the 9th grade level.

TABLE 21 Effects of Disruptive Peers at a class (Interaction term)

	NEET	No degree	Matriculation exam.	Crime in 8 years
Specification	(1)	(2)	(3)	(4)
Fraction of disruptive boy peers	0.049	0.101	-0.126	0.128
	(0.007)**	(0.007)**	(0.008)**	(0.007)**
Girl	-0.028	-0.036	0.192	-0.118
	(0.002)**	(0.002)**	(0.002)**	(0.002)**
Girl*Fraction of disruptive boy peers	0.006	-0.010	-0.054	-0.139
	(0.009)	(0.009)	(0.011)**	(0.008)**
Fraction of disruptive girl peers	0.027	0.043	-0.050	0.053
	(0.007)**	(0.007)**	(0.009)**	(0.007)**
Girl* Fraction of disruptive girl peers	-0.000	0.009	-0.090	-0.054
	(0.009)	(0.010)	(0.012)**	(0.008)**
cons.	0.344	0.276	0.276	0.205
	(0.004)**	(0.004)**	(0.005)**	(0.003)**
R^2	0.06	0.08	0.16	0.10
N	1,030,059	1,030,059	1,030,059	1,030,059
Year Fe	Yes	Yes	Yes	Yes
Class label Fe	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes
Mean Y	0.18	0.19	0.53	0.117

Note: **p<0.01,*p<0.05. Each column represents different regression. Robust standard errors in parentheses are clustered at the class level. Additional controls include gender, language, the amount of students in a class, own parents' criminality and parents' income.