Aalto University
School of Economics

Property Crime and Income Inequality in Finland

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ABSTRACT

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PROPERTY CRIME AND INCOME INEQUALITY IN FINLAND

The goal of this thesis is to study the relationship of income inequality and property crime rates in Finland. While theoretical expectations for the relationship are strong, empirical evidence from previous within-country studies is mixed.

My data set covers 337 Finnish municipalities during 1995-2009. The relationship of the Gini coefficient and crime rates was econometrically tested using an OLS model, a fixed effects panel data model and a dynamic generalized method of moments (GMM) model. The tests were conducted for property crimes in general, robbery, theft, embezzlement, fraud and violent crime.

I find income inequality to correlate positively with theft crimes. For other property crimes the evidence of a positive relationship is somewhat weaker. No correlation is found between income inequality and violent crime. Other factors determining differences in Finnish crime rates are those expected by existing literature: population density, unemployment rate and the proportion of foreigners in a population.

The results of my dynamic model support the hypothesis that criminal inertia is relevant in the study of determinants of crime. Static models may underestimate the effects of different regressors if their effect on crime rates is partly realized with a lag. Furthermore I find clear differences between crime types. On the basis of my work it seems clear that different types of crimes and their determinants should, whenever possible, be studied separately.

TIIVISTELMÄ

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OMAISUUSRIKOSTEN JA TALOUDELLISEN EPÄTASA-ARVON YHTEYS SUOMESSA

Tutkielmani tavoitteena on tutkia tulonjaon ja omaisuusrikosasteen yhteyttä Suomessa. Taloudellisen epätasa-arvon ja rikoskäyttäytymisen väliselle korrelaatiolle on vahvat teoreettiset odotukset, mutta empiirisesti yhteys on aiemmissa tutkimuksissa vahvistettu vain osittain.

Käyttämäni aineisto kattaa 337 suomalaista kuntaa aikavälillä 1995 – 2009. Tutkin Gini-kertoimen ja rikosasteen tilastollista yhteyttä yksinkertaisella ordinary least squares (OLS) –mallilla, paneeliaineistoa hyödyntävällä fixed effects –mallilla sekä dynaamisella generalized method of moments (GMM) –mallilla. Testit tehtiin erikseen omaisuusrikoksille yhteensä, ryöstörikoksille, varkausrikoksille, kavalluksille, petoksille sekä väkivaltarikoksille.

Tulosteni perusteella taloudellinen epätasa-arvo Gini-kertoimella mitattuna korreloi positiivisesti varkausrikosten kanssa. Muiden omaisuusrikosten kohdalla korrelaatio ei ole kaikkien mallien tapauksessa tilastollisesti merkittävä. Väkivaltarikosten ja tulonjaon yhteys on tulosteni perusteella olematon. Muilta osin erot kuntien rikosasteessa selittyvät myös aiemmissa tutkimuksissa relevanteiksi havaituilla muuttujilla, kuten väestöntiheydellä, työttömyysasteella ja ulkomaalaisten osuudella.

Dynaamisen mallini tulosten perusteella rikosasteen muutosten heijastuminen periodilta toiselle on relevantti tekijä rikosten tilastollisessa tutkimuksessa. Staattiset mallit saattavat aliarvioida eri muuttujien vaikutusta rikoskäyttäytymiseen, mikäli näiden vaikutukset todellisuudessa realisoituvat viiveellä. Lisäksi löysin merkittäviä eroja eri rikostyyppien välillä. Tutkimukseni perusteella näyttää selvältä, että omaisuusrikoksia tulisi tutkia rikostyypeittäin sen sijaan, että niitä tarkasteltaisiin yhtenä kokonaisuutena.

Table of contents

Tables and figures

1 Introduction

This thesis is a study of the empirical relationship of economic inequality and property crime in Finland. Economic theory suggests that there is a positive relationship between income inequality and crime. Inequality can be a source for criminal opportunities while at the same time representing poor opportunities for legal income for some individuals. Several sociological theories make similar predictions for the positive relationship between inequality and crime. These theories see the social tension and frustration caused by inequality as a motivational factor for crime.

Empirically the correlation between income inequality and crime has been found to be very strong in between-country studies. The evidence in within-country studies is substantially weaker. Depending on the approach chosen and the particular crimes studied, some econometricians have found a positive link between inequality and crime, while other studies have failed to prove such correlation. The lack of a strong underlying theory and several technical issues make the econometric study on the causes of crime a complex issue. It is therefore not surprising that the methods and results of various studies differ substantially.

The tremendous social and economic costs of crime have motivated a great deal of research on the topic. Studies examining the relationship of crime and for example, inequality, severity of punishment or youth unemployment all have clear policy implications. Authors such as Benoit and Osborne (1995) or Sala-i-Martin (1995) have taken a very direct approach of evaluating income distribution policies as crime-reducing tools. My econometric work will offer insight into not only the relationship between income inequality and crime in Finland, but other determinants of crime as well. As crime is a partly cultural phenomenon, this study will provide information on causes of crime in especially in a Nordic and Finnish context.

The empirical portion of my thesis uses municipal level data from Finland spanning the years from 1995 to 2009. The primary crime categories studied are aggregate property crime, aggregate violent crime, theft, robbery, embezzlement and fraud. The incidence rates of these crimes are regressed against the Gini coefficient and an array of other explanatory variables. My econometric specification includes typical socio-economic variables such as an education index and the unemployment rate. I will examine the crime rates using three different models. First, I describe the relationship between inequality and crime with a pooled ordinary least squares (OLS) model. Secondly a fixed effects model is used to control for possible omitted variable problem in simple OLS regressions. Finally, I employ a generalized method of moments (GMM) model in order to address the issues of criminal dynamics and endogeneity of regressors.

My results do not confirm a universal correlation between inequality and crime. Instead, I find strong evidence of a correlation between the Gini coefficient and theft crimes but somewhat weaker evidence for robbery and other property crimes. For violent crimes the correlation proves to be nonexistent. The regression results for the other determinants of crime are mostly in line with previous research. Property crime in Finland is positively correlated with unemployment, population density and to some degree the number of foreigners. The relationship between education and property crime rates is more complex as the general education index shows a positive correlation with crime in some specification. However the number of youth lacking higher education seems to be a good predictor of crime rates.

The structure of the thesis is the following. In chapter 2 I present a discussion on the economic theory of criminal decisions and introduce relevant sociological theories. Chapter 3 offers a brief summary of previous research on the topic of inequality and crime. In chapter 4 I introduce the models used in the econometric portion of the thesis and discuss the variables used in the regressions in-depth. These models are put into use in chapter 5, where I present the data and the results from the regressions. Finally, chapter 6 offers some concluding remarks on my work and findings.

2 Theoretical framework

I will next present a summary of the theoretical discussion concerning the determination of crime. Chapter 2.1 will first present the typical economic approach to the question of criminal behavior. Other relevant theories in the field of criminology are discussed in chapter 2.2. A more detailed analysis of how the relationship between inequality and crime works in the various theoretical frameworks is offered in chapter 2.3. Chapters 2.4-2.5 summarize two key issues relevant to understanding the relationship of inequality and crime: heterogeneity of crimes and the dynamic nature of crime.

2.1 Economic theory of crime

The starting point of modern economic study of crime is often seen in the pioneering seminal article by Becker (1968). The Beckerian model has individuals comparing expected returns from criminal activity to the returns from participating in the labor market. This framework still forms a base for many econometric studies. In effect it is a one-period model of decision under uncertainty, where illegal activities are considered as risky projects. The risk inherent in crimes is modeled as a possible monetary fine or imprisonment. At the very heart of the classical economic approach is the thought that criminals respond to incentives like all other economic agents. An adequate change in social conditions will thus change the tradeoff sufficiently for agents at the margin to either induce or inhibit criminal behavior. Most of the classical economic models allow for heterogeneity between agents in terms of income-earning abilities, risk preference, respect for law (Ehrlich, 1973), inclination for violence or other characteristics.

While theorists following Becker's example work with a supply of offenses functions, others have modeled a police expenditure function or resource allocation and punishment setting through collective decision-making. For example, in Benoit & Osborne's model society chooses the levels of punishment by optimizing the utility of each member of the society. This model predicts that factors such as income inequality have an effect on the severity of punishment for different offenses. (Beinoit & Osborne, 1995)

Another typical variation is a portfolio choice setting, where agents allocate resources between risky criminal projects and non-risky work. A popular and simple example of such an approach is a tax evasion case, where a choice is made concerning the optimal amount of income to report to the authorities. At the margin, a decrease in reported income reduces tax costs while increasing the risk of punishment. Eide offers a long list of authors who have modeled a similar situation (Eide, 1994).

Extensions of Becker's framework differ in formulation of the decision but many also include dynamics or relaxing some assumptions on rationality (see for example Eide, 1994; Garoupa, 2003). Allowing for bounded rationality is a step towards non-economic theories of crime, many of which see personal characteristics as being a cause of criminal behavior. Criminals are frequently claimed to be more inclined to act on impulses, be myopic or overconfident about the risk of apprehension (Virén, 2000). Several authors suggest that bounded rationality is often a more fitting representation of criminal behavior than rational choice theory (see for example Shover & Honaker, 2009; Nagin & Paternoster, 1993).

The direct monetary gains from crime vary with opportunities for crime, individual's criminal skill and the secondary market for stolen goods. In an economic model that also incorporates psychological benefits, agents engage in criminal activity in part because they receive direct utility from criminal activity. This is often called the "taste for crime". Siegel notes that the thrill of "getting away with it" often acts as a motivation for crime. Siegel goes on to suggest that even murder can have an emotional payoff (Siegel, 2003, p 192). Eide (1999) gives a list of additional psychic benefits of crime such as the thrill of danger, retribution and peer approval. The expected cost of committing a crime on the other hand consists of the probability and severity of punishment as well as reputational and psychological costs. The expected punishment of crime has been focus of Becker and many subsequent authors who have made the effect of deterrence variables on criminal activity a central part of their work. Punishment in the form of incarceration bears a greater cost to those with higher potential for legal income since this opportunity is forgone during the time spent in a prison. Deterrence variables are discussed in-depth in chapter 4.2.3.

Convicted and even suspected criminals face reputational costs in the job market as well as amongst their social contacts. The labor market reputation cost is directly correlated with the agent's skill level. Sala-i-Martin (1995) also notes that jobs requiring trust tend to have higher wages. The psychological costs as well as benefits are generally seen as having great importance for criminal decisions. Furthermore it is typically assumed that these costs vary intensely between individuals, but remain constant across periods. This assumption may be challenged by introducing norm formation.

The Becker model and its extensions can easily be seen as insufficient in light of empirical evidence. Different theoretical frameworks are used by even practitioners trying to answer similar research questions. This points to lack of a strong theoretical base for econometric research. The various theory of crime models are very specific in terms of the situational factors that they can be applied in. Violent crimes and property crimes are often examined with a similar framework, yet the empirical results are contradicting. For example, in the American setting drugs, gangs and racial issues often dominate the discussion and research on crime. These issues weigh much less in a Nordic context.

Economic models have received critique for being inadequate in explaining violent crime (see for example Kelly, 2000) but also - and perhaps more importantly - juvenile crime. In many models labor market opportunities are given great importance in explaining crime, and yet they have little relevance to teenagers. Young people participate in crime long before they participate in the labor market. Paternoster (1989) found deterrence variables to have virtually no effect on adolescent decisions concerning crime. These kinds of observations are critical considering the fact that criminal patterns emerge at a very young age and are very persistent. The strongest critique against the economic model is the one made against the assumptions the model is built on. Authors such as Garoupa (2003) see it evident that there is a "gap between the rational theory and actual behavior of criminals". The assumptions of amorality, perfect information, and unbounded willpower are amongst the many that Garoupa finds too strong to describe criminal behavior. If criminals were in fact acting as profit maximizing agents, we would not witness criminal remorse. According to Eide (1999) it may also be unrealistic to assume correct beliefs about the punishment variables. The rational choice framework nevertheless expects behavior to reflect marginal changes on the probability of conviction and severity of punishments.

2.2 Sociological theories of crime

While economists naturally study the subject of crime with the tools they are most familiar with, they cannot dismiss the findings of other disciples of science. Criminals act like profit maximizing agents up to a certain extent, but it would be foolish to ignore other sources of motivation that come into play in crime-participation decisions. Erling Eides model of norm-guided rational behavior is a great example of the much needed effort in the study of criminal behavior to bridge the gap between sociology and economics (Eide, 1994). Sociological theories should not be overlooked simply because they do not fit conveniently into the economic model. As is relevant to my thesis, these theories offer valuable insight into the possible relationship between inequality and crime, but they also motivate the use of certain control variables often employed by econometricians. Many economists see the economic and criminological approaches complementary rather than conflicting (see for example Carr-Hill & Stern, 1973 or Bushway & Reuter, 2008).

The scientific study of crime, criminology, is rich with different theories on the determinants of crime. In criminological literature the economists' approach is often categorized under the moniker of rational choice theory (see for example Siegel, 2003) while economists often refer to non-economist theories simply as "criminological theories". For an in-depth discussion on the relationship between the economic study of crime and other criminological work, see Bushway and Router (2008). Next I will present a summary of social disorganization theory and strain theory. Both of these theories predict a positive correlation between income inequality and the level of property crime. The final portion of this chapter contains a very brief introduction to routine activity theory and differential association theory.

Social disorganization theory was popularized by Clifford Shaw and Henry McKay in the 1940's. The theory describes the breakdown of crime-preventing social controls in communities. Shaw and McKay argued that fluctuations in the crime rate are largely caused by poverty, residential mobility and ethnic heterogeneity. In addition to bringing focus from the individual level to the community, Shaw and McKay were able to show that changes in crime persisted over many years even after the initial "shock" was long gone. (Shaw and McKay via Sampson & Wilson, 1995) For a more recent view on the state of social disorganization theories, see Kubrin and Weitzer (2003). In an econometric setting social disorganization may be, and has been, proxied by the percentage of homeowners versus renters, level of ethnic heterogeneity, population turnover etc. In Sampsons and Wilsons (1995) view inequality causes social isolation which in turn weakens the level of social organization that plays an important part in preventing crime. Siegel (2003, p. 195) refers to a study by Chamlin and Cochrane that found institutional ties such as the church to have a preventive effect on crime. Hirschi (1986) sees ties to all institutions as well as the family and friends as critical in preventing crime. The relevance of social control is also acknowledged by economists such as Levitt and Lochner (2001).

Strain theory, first introduced by Robert Merton, sees criminal activity stemming from social pressures on individuals. One such source of pressure is economic disparity, which is very often called “relative deprivation”. According to strain theory crime is partly motivated by feelings of disadvantage and unfairness that are aggravated by economic and social inequality. (Merton, 1938 via Burton, Evans & Dunaway, 1994). The general trail of thought that runs through strain theory is often echoed in publications that do not directly acknowledge Mertons work or explicitly mention strain theory. The importance of relative income is widely studied, but strain theory acknowledges other sources of strains on the individual. For example Agnew (1984) focuses on the failure to achieve goals such as money or status. These kinds of strains are much harder to operationalize than relative deprivation, which can be represented very well by common inequality measures. As social, political and economic aspects of equality often go hand in hand, it is not surprising that economic equality is quite often chosen as the sole measure of relative deprivation.

The effect of relative deprivation is to some extent empirically testable. Relative deprivation, in contrast to many other explanations for crime, is expected to affect individuals throughout the income distribution instead of just the poor. Allen (1996) notes that even “individuals who could earn a better living in a legal endeavor will be predisposed to criminal acts if they perceive unjustified deprivation relative to a reference group in the society.” Likewise, correlation of poor on poor crime and inequality, can be explained by relative deprivation but not, for example, by the amount of criminal opportunities. Verifying any such hypothesis does, however, require micro-level data.

As mentioned, the field of criminology is rich with theories many of which are relevant to the discussion of inequality and crime. Next I will briefly go through routine activity theory and differential association theory.

Routine activity theory holds that opportunities for crime are the single most important factor while variables such as unemployment or poverty should not have much effect on criminal activity (Cohen & Felson, 1979). If this were true then the positive effect of income inequality on criminal opportunities would be the primary explanation between the link often found between inequality and crime. Opportunities for crime are discussed in chapter 4.2.2.

Finally, the theories of differential association and social learning assert that techniques, motives, values and attitudes for crime are learned through intimate personal groups (Burton, et al., 1994). Likewise people learn anti-criminal patterns from their environment. While factors such as unemployment affect only a limited amount of individuals, they might have a secondary effect on the rest of the community through social influence. This is contradiction to the assumption of stable preferences which is quite convenient for economic modeling. The possibility of learned patterns would also cause criminal inertia on an aggregate level. In other words, some areas simply might foster a culture of crime. This trail of thought is continued in chapter 2.5, which discusses the dynamic nature of crime.

2.3 Inequality and property crime

Although the positive relationship between economic inequality and crime is a common assumption among economists and criminologists alike, there are several versions of the description of this relationship. In this chapter we will discuss the exact manners in which inequality is expected to have an effect on criminal behavior. We can distinguish three distinct motifs offered for the relationship: opportunities for crime, opportunities for legal income and psychological motivation.

Criminal opportunities are expected to increase as well off individuals are placed in proximity with poorer individuals. Criminal behavior may, depending on the model used, be further escalated by lower opportunities for labor income for those at the lower end of the income spectrum. As the opportunity cost of crime is labor income, it is commonly argued that an increase in legal income opportunities makes the time spent incarcerated and out of the job market more costly (see for example Lochner & Moretti, 2004). For different models that deal with the relationship between the level of crime and the distribution of income, see for example Chiu and Madden (1998), Benoit and Osbourne (1995) or Sala-i-Martin

(1995). All of the models mentioned predict criminal behavior to increase as the income distribution becomes more unequal.

A skewed income distribution might also be a sign of low income mobility and poor future prospects for skilled poor individuals. The relevance of long term income prospects is also discussed by Bourguignon, who sees that “absence of income and social upward mobility [...] may be as important as relative poverty at a given point of time to explain criminality at the bottom of the income scale.” (Bourguignon, 1999) The stunted opportunity could also act as a catalyst for a sense of relative deprivation. Relative deprivation is one of the leading explanations for the psychological relationship between inequality and crime. The frustration caused by comparisons with other and the feeling of deprivation in terms of what is regarded normal in ones community may manifest in crime. For a more in-depth explanation for why relative deprivation could cause crime, see the previous description of strain theory in chapter 2.2.

While economists such as Kelly acknowledge the potentially large psychological effect of inequality on crime, economists generally focus more on the economic motivations altered by inequality (Kelly 2000). Trying to fit the assumptions made by theories such as social disorganization theory or strain theory into an economic framework is not always straightforward. In part, this could be done through changes in an attribute that describes an agent’s tendency for crime. Changes in social pressure or one of the many environmental factors could be simplified by altering just one variable: change in the threshold for crime. In Becker’s framework this could mean variation in the psychological income/loss attributed to committing offenses. Bourguignon et al. use a similar parameter called ‘honesty’ to capture differences in attitudes (Bourguignon, et al., 2003). For practical reasons authors such as Becker worked under the assumption that these preferences differ between individuals but are stable between periods. Sociological theories differ in this aspect as they see certain attributes as being subject to peer influence and external factors. If the psychological cost of committing crime is indeed subject to, for instance, economic inequality, then this would warrant a more complex model.

2.4 Heterogeneity of different crime types

Intuition alone tells us that one type of crime differs greatly from another one in many characteristics. Crimes are heterogenous in the inherent risk and reward, expertise required, psychological costs and many other aspects. Aggregating different types of crimes thus means losing a lot of information in the process. According to Entorf and Spengler (2002)"Aggregate crime rates are almost meaningless. They give a murder the same weight as the theft of bicycle, so that the variation of property crimes dominates the time series fluctuation of overall crime rates". On the basis of her empirical work, Edmark also finds that trying to explain aggregate crimes is very fruitless in comparison to examining individual crimes (Edmark, 2003).

A classical way to classify crimes is to separate crimes against property and crimes against the person. Eide (1994) makes a distinction between "expressive" crimes such as rape or arson and "instrumental" crimes - namely non-violent property crimes - and a wide spectrum of crimes with a degree of each element. Rational behavior models are typically seen as having more explanatory power for instrumental crimes than expressive ones. Many crimes also require a very specific skill set. In studying these type of crimes we might take into account theories of differential association (see chapter 2.2), where information on criminal techniques is passed on from one individual to the other. On the other hand, crimes such as tax evasion are available to anyone willing to break the moral code and risk punishment. Parallel qualities can be seen in exaggerated insurance reports and many other non-violent "victimless" crimes.

The psychological cost element of crime was discussed in chapter 2.1. In these aspects individuals as well as crimes may be very heterogeneous. Property crimes that require the threat or use of violence can be expected to come at a great psychological cost to most individuals. Likewise, social stigma and reputational costs might vary according to crime type. Among property crimes, one might imagine different attitudes towards crimes against a single person versus crimes against a large entity such as a large corporation or the state. Indeed justification may act as a motivation in offenses where the criminal takes back from an employer or an insurance company that they feel has gained from them in the past.

Different types of crimes are typically committed by different people. In Benoit and Osbournes framework crime rates of different crimes vary in their elasticities to income distribution. The elasticity is determined by the relative incomes of the individuals who tend to commit a crime of a particular type. Their model predicts that certain crimes that the rich people are sensitive to could be rare in an unequal society while the same circumstances might lead to a high crime rate in poor on poor –crime. (Beinoit & Osborne, 1995)

Finally, not all crimes are reported to the police with the same likelihood, nor are they as likely to be solved. Virén mentions shoplifting as an interesting example: shoplifting is reported mainly in cases where the criminal is caught red handed. Thus the clear up rate for shoplifting is close to a hundred percent. (Virén, 2000) We must also take into account the possibility that crimes differ in the way they are investigated and treated in the criminal justice system. For instance, the Finnish data set suggests that tax evasion cases are caught and punished with a very sizeable lag.

2.5 Dynamics of crime

There are strong grounds to assume that crime in previous periods influence the current period for both individuals and communities. The beginning of this chapter will deal with arguments that suggest individuals to be path dependent on their choices regarding crime. After this I'll discuss criminal inertia on a community level. An empirical test on the effect on dynamics is conducted in chapter 5.5

Any model that has individuals comparing the costs and benefits of crime predicts a high rate of repeat offenses. If preferences are stable and economic conditions are similar before and after incarceration, previous offenders are expected to return to crime. Sala-i-Martin offers the counterargument that criminals might find the reality of prison life harder than previously thought, thus leading to an increase in the perceived penalty after an individual has been incarcerated (Sala-i-Martin, 1995). However, if human capital is accumulated at the workplace, people who devote their time to crime instead of work will suffer a severe handicap at the labor market (Flinn, 1986). At the same time their acumen in property crime can possibly lower their risk of getting caught as well as increase the potential gains from crime. The payoff gap between legal work and crime might thus widen with every criminal act. Eide quotes a study by Wilson and Hernnstein (1985) that highlights the fact that the majority of career criminals have first started with crime at a very early age (Eide, 1994). This result might be explained by personal characteristics, path dependency or both.

Williams and Sickles use an earnings function where individual social capital stock includes aspects such as reputation and social networks (Williams & Sickels, 2008). An individual that has a low capital stock in these terms (a known criminal) has less to lose from further acts of crime. Reputation and social networks are of course advantageous to even individuals whose earnings do not directly depend on them. As Garoupa puts it, criminal life has high exit barriers (Garoupa, 2003).

Rational choice theory usually assumes norms and preferences to be stable. While this is certainly convenient for the purpose of modeling, in the context of crime this assumption may prove to be quite far from reality. Several sociological theories such as differential association explicitly build on the very idea of unstable or interdependent preferences. Such theories work under the assumption that peer influence or other environmental factors play a large role in causing or preventing crime through their effect on norms and attitudes. Eide (1999) sees the role of norm formation as being a critical part in determining criminal behavior. In the short term norms are usually seen as fixed, but as we extend the time period, the investigation of norm formation becomes ever more relevant. Eide offers the poor success of criminal rehabilitation programs as anecdotal evidence of the persistence of preferences. In contrast, Ehrlich theorizes that the preferences for crime are not necessary stable but could even intensify with time (Ehrlich, 1973). This could mean, for example, the distaste for violence or breaking societal norms being dissolved as one grows numb to these matters.

It is another question altogether whether criminal activity in a community will cause more criminal activity in subsequent periods. If more crime is to be expected, the community might react in a number of ways that deter crime. First, individuals might invest more in personal protection (Demombynes & Özler, 2005). Second, the community might introduce harsher punishment for criminals. A third possible response would be to allocate more resources to law enforcement. It is also critical to note that many socioeconomical factors and crime are jointly endogenous with a very high probability. High crime areas could arguably deter both business and affluent, high-skill individuals. The links between, for example, crime and unemployment and crime and education are likely to work in both ways. As an example of the many ways crime affects a society, Sala-i-Martin (1995) argues that crime lowers labor productivity since victims are often emotionally and physically disrupted. For a more detailed study on the effects that crime has on a community, see Entorf and Spengler (2000).

3 Summary of previous research

Econometric studies on crime - often grouped under the name of criminometric studies - are found in abundance. The focus point of existing research varies, and it is easy to find a large number of papers that focus on, for instance, deterrence variables, income opportunities or sociological factors. This chapter includes a summary of those studies that directly address the relationship between inequality and crime. The range of methods employed in related studies is discussed at the end of the chapter. For a general overview of previous criminometric work not limited to only inequality and crime, see Eide (1994) or Soares (2004).

Existing studies on the relationship between inequality and crime generally focus on estimating the magnitude of the relationship while sidestepping the issue of verifying the underlying theory. This is understandable, as the relationship has important policy implication regardless of which theoretical framework is the most appropriate. Furthermore we need to note that statistically determining the relative importance of psychological, social and economic motivations for crime is a very hard task. One testable implication of many sociological theories is that they suggest that poor on poor crime is also very highly positively correlated with inequality. Such test would, however, require the use of micro level data.

The clearest statistical correlation between inequality and crime has been found in studies that use countries as the level of aggregation (see for example Fajnzylber, et al., 2002; Soares, 2004). In fact, Soares (2004) found income inequality to be the single most important variable to explain between differing crime rates between countries. Studies focusing on variance between states, municipalities or cities tend to show significantly smaller correlations that at times fail to exhibit statistical significance. Among within-nation panel data studies that found evidence of a positive correlation between inequality and property crime are Nilsson (2004), Imrohoroglu, Merlo and Rupert (2000). Several studies find no evidence between measures of inequality and the crime rate. One such study is by Allen (1996), who failed to find a positive link between inequality and property crime. Studies that do not study the direct effects of inequality but instead focus on the percentage of percentage of low-income households or individuals are also very commonplace. Ehrlich

(1973) found that crime, especially property crime, varies positively with the percentage of households in the lowest income quartile. A link between poverty and crime is also found by Bourguignon et al. (2003).

Several authors have found mixed evidence for the correlation of crime and inequality. A cross-sectional study by Kelly (2000) found only weak evidence between inequality and property crime in urban areas in the US (violent crime and inequality were, however, strongly correlated in Kelly's study). Brush (2008) found a positive correlation between inequality and crime in a cross-sectional analysis but failed to find significant evidence in his 10-year time-series analysis. Choe (2008) finds burglary to correlate strongly with the Gini coefficient, but fails to find a similar relationship with aggregate property crime. Dahlberg and Gustavsson (2008) found that permanent income inequality does indeed correlate with criminal activity, but changes in temporary income do not. They raise the very important point of separating between long-term trends and temporary shocks to income and income inequality. In the case of violent crime, results are perhaps even more contradictory than for property crime. Among authors that found inequality to be an important determinant for violent crime are Fajnzylber, et al. (2002) and Saridakis (2004). Meanwhile authors such as Neumayer (2005) and Kelly (2010) fail to find a link between inequality and violent crime.

The arsenal of methods used for criminometric work is large and includes time-series, cross sectional and panel data utilizing both micro and macro level data. Criminometric studies also have large differences in the way they address the important question of variable selection. Even among authors that base their econometric studies on the causes of crime on similar theoretical frameworks, the instruments used in the econometrics analysis differ greatly. Entorf and Spengler (2002) give a detailed summary of the expected effects of different variables on crime as proposed by existing literature. See Eide (1994) for a summary of the different variables used by practitioners. Naturally the choice of variables is sometimes determined not by their fit to the underlying theory but by their availability. Keinänen (2004) notes that the while most theories offer predictions of criminal behavior at the individual level the datasets available are typically aggregated.

Numerous studies on the determinants of crime have been conducted on both micro and macro data. There are very good arguments for both approaches. As Eide (1994) points out, economical theories of crime tend to describe behavior of the individual and it is thus natural to use micro level data to verify them. Macro level data often suffers from many statistical problems, such as the identification problem of simultaneous decision making by potential victims, criminals and authorities (Keinänen, 2004). Testing the validity of a certain micro model forces the use of very restrictive assumptions such as the "representative individual" (Eide 1994). Macro studies do, however, have a very direct link to policy considerations. If we are to estimate a particular elasticity to the rate of crime or even the cost of crime in a society, a macro study is a very direct way to address the question.

Micro level data is available in Finland in the form of national victim surveys (last conducted in 2009, 2006 and 2003) and surveys based on self-reported criminal activity. Studies that employ micro level data provide important insight on the characteristics of offenders that is highly relevant in all criminometric work. The relationship of income inequality and crime is, however, not a typical research question for micro studies. One interesting exception is a study by Buettner and Spengler, which attempts to make a distinction between the effect of inequality to criminal opportunities and the possible effect of inequality to psychological motivation. They do this by studying the effect of inequality on resident and non-resident criminals separately. Buettner and Spengler's findings suggest that inequality does indeed cause crime both because of its effect on criminals and its effect on possible criminal targets. (Buettner & Spengler, 2003)

My econometric work in the following chapters makes a distinction between eight different crime categories and finds that different crimes are driven by different socioeconomic factors. Comparison with existing work is not straightforward as the crime categories studied by authors differ, as do their definitions. In addition to the aggregate crime categories of property crime and violent crime, theft and robbery are the two best candidates for comparison between other studies. As will be evident in the discussion of my results, the most commonly studied and clear-cut categories of property crime and violent crime are too general to offer the most insight into crime determination.

4 A model for econometric analysis

The primary purpose of this study is to estimate the causal relationship between income inequality and crime in Finland. In this chapter we move forward towards this goal by building a model of crime determination. Some variables are discussed are ultimately omitted from the model specification or only represented by weak instruments. One such topic is the deterrence effect, which has been a central focus of criminometrics in general, is but given very little weight in this study. The relevant variables discussed next are put to test in chapter 5, where the empirical results are reviewed.

In chapter 5 I will present the results of three sets of regressions for a number of crime categories. First, I study the effects of inequality on crime using an OLS model. The model will include an array of explanatory variables and a yearly dummy Υ_t to control for national trends in crime. To be able to properly isolate the effect of income inequality we must take into account the control variables as a vector π_{kit} in equation (1). Equation (1) assumes all nine control variables are employed. The resulting model can be stated as:

$$\ln C_{it} \;=\; \gamma_t + \beta_1 \ln G_{it} + \sum_{\{k=2\}}^{11} \beta_k \ln \pi_{kit} + \varepsilon_{it} \qquad (1)$$

The second model I use is a fixed effects panel data model. To amend (1) with unit specific fixed effects, we assume that the error term ε_{it} may be divided into unobserved area specific fixed effects $\propto_i$ and observation specific errors ω_{it}. Crime is thus expected to be partly caused by unobserved qualities in each unit - in this case municipality.

$$\varepsilon_{it} \;= \propto_i + \omega_{it} \qquad (2)$$

The fixed effects approach lets us work around the possibility that the model would otherwise suffer from omitted variable bias. It is possible that the Gini coefficient and other regressors are correlated with certain important differences in the municipalities that also play a part in determining the crime rate. A key assumption for such between-area differences is that they be time-invariant. Prime examples of differences that do not change over time include geographical considerations, such as proximity to national borders and neighboring municipalities. Effects that are very time-invariant, but not strictly fixed, include popular tourist attractions, the presence of particular industries, certain demographic variables etc.

Measurement error is a well known problem with criminometric work that also motivates the use of a fixed effect model. Crime underreporting is likely to be vast and to correlate with factors such as education, urbanization rate and inequality. The part of underreporting that is not correlated with the regressors, but constant on a per municipality basis (systematic error), will be captured by the fixed effects model. Equation (3) describes criminal determination as assumed by the fixed effects model. With the exception of separating the municipality specific term $\propto_i$ from the error term, equation (3) is identical to (1).

$$\ln C_{it} = \alpha_i + \gamma_t + \beta_1 \ln G_{it} + \sum_{\{k=2\}}^{11} \beta_k \ln \pi_{kit} + \omega_{it} \qquad (3)$$

In the third set of regressions we take into account the possibility that crime is serially correlated. This assumes a correlation between C_{it} and C_{it-1}. The model applied is an Arellano-Bond Dynamic Panel GMM estimator. We amend (1) with the lagged crime term and take first differences of all the regressors. Unobserved fixed effects no longer enter the equation as they are by assumption constant between periods. Changes in criminal activity are now assumed to be represented by equation (4).

$$\Delta \ln C_{it} = \beta_1 \Delta \ln G_{it} + \beta_2 \Delta \ln C_{it-1} + \sum_{\{k=3\}}^{12} \beta_k \Delta \ln \pi_{kit} + \Delta \varepsilon_{it} \qquad (4)$$

All three approaches are routinely employed by criminometricians. Together they offer a comprehensive look into the determination of crime in a Finnish context. The results produced by the three models are discussed in their specific chapters, 5.3.-5.5. What follows next is an overview of the variables used in the regression models. The variables are chosen according to theory and findings in other statistical studies. For the purpose of this study, data availability does not pose a serious hurdle. The set of instruments used represents to a large degree the optimal set that would be chosen by the author in the absence of data limitations. Robustness of the findings could however be better ensured with the inclusion of secondary measures for inequality and additional deterrence variables.

4.1 Dependent variable, crime rate

The dependent variable *C* represents the number of crimes in a municipality, as reported to police, divided by 100 000 inhabitants. This approach to measuring crime, while being a standard one, is by no means perfect. Perhaps the largest source of error in reported crime statistics stems from crime underreporting, which need not be homogenous between areas, periods or crime types. As Witte and Witt noted, underreporting is "strongly correlated with factors affecting crime rates such as inequality, education, the average level of income, and the rate of urbanization"(Witte & Witt, 2001). According to estimates by the OPTL, roughly half of thefts in Finland are reported to the police. The single most important motivator for reporting thefts is the chance of gaining insurance payments. (OPTL, 2011) We can also expect a correlation between underreporting and the perceived clear-up rate of a particular crime type. A victim of a crime that expects a low probability of the crime to be solved is more likely to forego reporting (OPTL, 2011).

Keinänen (2004) refers to studies that find American police districts to differ in the way they classify different crimes. Crime classification may differ systematically from one area to the next. In some instances it is also up to the discretion of officers if a particular criminal act is interpreted as multiple crimes or just one. Victimization studies and other alternative approaches to estimating the rate of crime such as are discussed in Keinänen (2004).

4.2 Explanatory variables

4.2.1 Income inequality

The regressions use a Gini coefficient of disposable income, G_{it}, as a measure of inequality. Although the use of Gini coefficient is the most common choice of practitioners to measure inequality, alternative instruments are also found in the empirical literature. To name just one such example, Ehrlich (1973) discusses using mean income versus median income, but due to statistical considerations chooses to use the percentage of families below one half of the median income in his model. The Gini coefficient nevertheless has very strong theoretical appeal. In total 13 out of 15 studies presented by Soares chose to use it as a primary measure of inequality (Soares, 2004).

An alternative course of investigation is to look at the causes of income inequality and study whether these factors are directly linked to crime. Kelly (2000) constructed an educational Gini coefficient to measure educational inequality within urban US counties. Fajnzylber et. al. (2002) use standard deviations of average schooling years in their cross-country analysis. Entorf and Spengler (2002), on the other hand, use the ratio of high qualified labour force to low qualified labour force as a metric of inequality. The strongest case against using the Gini coefficient as a sole measure of inequality is made by Wolfson (1994) as well as Esteban and Ray (1994), who both argue that two areas with the same level of inequality as measured by the Gini may have very different degrees of bipolarization. According to those claiming that polarization should receive more attention, population segments that are distant from each other but homogenous among themselves are a cause of social tensions and crime.

A distinction can be made between the direct effect of inequality on crime and that of poverty on crime. While it is a typical assumption that an unequal income distribution correlates with a high instance of poverty (see for example Kelly 2000), many scholars choose to focus on the fraction of population that is responsible for a large share aggregate crime. Bourguignon (1999) simplifies this view quite well when he states that “the rate of crime should be a function of both the relative poverty headcount and the relative poverty 'shortfall'”. By poverty shortfall Bourguignon means the resource gap between a group defined as poor and the median of the population. A skewed income distribution is often related with a high instance of poverty but this need not always be the case. Bourguignon et al. (2003) found that “would be criminals in Colombia were to be found among those households where income per capita was below 80 per cent of the mean”, and that changes outside this particular group had very little effect on aggregate crime. Likewise Nilsson found a positive relationship between the number of people with income below 10 percent of the median and the crime rate. The same panel data from Swedish counties shows that the Gini coefficient as well as variables based on percentile quotient ($90^{th}/10^{th}$) produced insignificant effect on crime. (Nilsson, 2004)

The results listed above suggest studying the effect of inequality by examining the relative sizes of different population segments. While examining different income segments is omitted from this paper, I will use the relative sizes of several “high-risk” groups, such as the unemployed or the relatively poor, in a municipality as a control variable. These groups are discussed in depth in chapter 4.2.2.

4.2.2 Opportunities for legal and illegal income

The regressions employ three explanatory variables that I classify as income variables: average municipality income divided by the national average, general unemployment rate and the municipality poverty rate[1].

According to the economic theory of crime, opportunities for both legal and illegal income play a crucial part in determining the crime rate. Selecting the right proxies for these opportunities is not straightforward. Choe and Chisholm (2008) see ambiguity in the use of income variables as being one of the essential problems of econometric research on crime. For these reasons the choice of relevant income variables deserves a closer inspection. The opportunities for legal income vary with the individual’s abilities, racial background, and gender as well as macro variables such as the general unemployment rate. The range of proxies that have been used by economists to measure labor income opportunities is even wider than in the case of income inequality. Eide lists median family income, median income, labor income to manufacturing workers, mean family income, mean income per tax unit, mean income per capita as some examples of the many proxies for legal income opportunities (Eide, 1999). It is important to note that many of these variables correlate heavily with inequality, average income and each other.

Unemployment is a key indicator according to the economic theory of crime. Exclusion from the labor market means that the opportunity cost of crime is substantially lower than for those that can allocate their time to attaining income through legal means. Expectations of future job prospects may also be derived from the unemployment rate. Sociological theories also predict unemployment to cause crime as the frustration caused by unemployment provokes criminal acts. Even though the theoretical link between unemployment and crime is strong, empirical results between the two variables are mixed (see Eide 1994 for a

[1] Households with an income that is less than 60 per cent equivalent national income in any given year

summary). The unemployed certainly have poor opportunities for income and at the same time more free time to commit crimes (Machin, et al., 2011). However, Cohen and Felson (1979) have theorized that unemployed people also spend more time home guarding their property and surveying the neighborhood. High unemployment could thus lower the viable targets available for crime.

As a large part of crimes are committed by low socio-economic classes and the young, measuring income opportunities for these groups is well justified. This can be done, for example, by the inclusion of variables such as low-skill wages, as done by Machin and Meghir (2000). In my model, youth unemployment will be tested as an alternative explanatory variable to the general unemployment rate. In the Finnish context social security benefits can be seen as an important source of income. Sala-i-Martin argues that social security is crime reducing not only because it narrows the gap between legal income and illegal income but also because it acts as an opportunity cost to committing crimes. The amount of benefits received is the amount criminals miss out if they are caught and jailed. (Sala-i-Martin 1995). Nilsson (2004) argues that poverty is a more long-term condition than unemployment and for this reason income inequality is a better proxy for job market opportunities than unemployment. If we are to follow Nilssons reasoning and look for permanent signals of poverty to explain crime, one option would be to use a lagged unemployment rate, as done by, for example, Britt (1997).

Additional points of focus could be available outside options and long term prospects for the high-risk group of potential offenders. Alternatives to crime such as self-employment, seasonal work and participation in the unreported economy might vary substantially between areas. Furthermore the long-term employment opportunities for unskilled workers could in part explain variance in crime rate. The effect of long-term opportunities might be studied, for example, by identifying areas with a high concentration of jobs in declining industries.

It is a natural expectation that increased opportunities for crime have a positive impact on the crime rate. Routine activity theory takes an even stronger stand than the economic perspective. According to routine activity theory opportunities for crime are the primary source of variance in the crime rate (Cohen & Felson, 1979). Measuring criminal opportunities for empirical purposes is very problematic. Opportunities for crime can vary, for example, with the general income level, income inequality and the effort individuals put into protecting their property. Several attempts have been made to finding an instrument for opportunities for crime. For example, Ehrlich (1973) used transferable assets as a proxy for the potential for income for activities such as robbery and theft. Other measures for criminal opportunities include total ratable value per acre (as done by Carr-hill and Stern, 1973) and the average value of stolen goods (Choe & Chisholm, 2008). We might see the opportunities for property crime as being influenced by variables such as the amount of vacation homes in the area, the efficiency of a secondary market for stolen goods or even the number of discotheques in an area (as assumed by Buettner & Spengler, 2003).

Using income variables to measure criminal opportunities is problematic in the sense that they correlate with labor income opportunities as well as the loss of foregone income in the case of incarceration. Income is also expected to affect the level of private protection from crime. Choe and Chisholm criticize the use of separate proxies for legal opportunities and illegal opportunities. They argue that since the relevant factor for crime is the difference between the two sources of income, this is the only variable that should be examined. (Choe & Chisholm, 2008) Entorf and Spengler try to work around the issue by using real gross domestic product per capita to measure opportunities for illegal income. To separate illegal opportunities from legal ones, they proxy labor income opportunities by a variable that compares real gross domestic product per capita to the national average. According to this view, legal work is more easily attained and wages are better in relatively rich areas. (Entorf & Spengler, 2002) In my work the variance in criminal opportunities will be represented by average municipality income compared to national average as well as the Gini coeffcient for income. However, for the purpose of measuring criminal targets, a Gini coefficient for the distribution of wealth would arguably be a more accurate measure than the Gini coefficient for disposable income.

4.2.3 Deterrence variables

The theoretical framework of criminal activity predicts individuals to respond to the deterrent of getting caught and punished. As the deterrence variables are very significant from a policy point of view, testing their effect on criminal behavior has been a central focus of Becker and many subsequent scholars. Criminals are often found to be risk-lovers in the sense that a rise in the probability of punishment has a more drastic effect on crime than increasing the severity of punishment (see for example Virén, 2000; Becker, 1968). In a time-series study covering Finnish counties for the years 1951-1955, Virén found a substantial effect of both the clear-up rate and the severity of punishment.

The use of deterrence variables such as the severity of punishment, police resources or the clear-up rate (percentage of crimes solved) as explanatory variables for crime is a very common approach in empirical studies. The variables mentioned do, however, pose several serious caveats. First, none of these variables can be assumed to be exogenous. The severity of punishment, the allocation of police resource and the level of private protection are all influenced by the rate of crime. Eide (1994) adds another insight by assuming that a society that chooses to assign unusually severe punishments to a certain type of crime might simultaneously signal its members that this particular act is exceptionally detrimental to the community. The level of sanctions might thus be a partial cause, not just the outcome, of societal norms.

The problem of simultaneity between police resources and crime level is so strong that it is even possible to find a positive correlation between police resources and crime. The simultaneity issue seems to make using police resources as an explanatory variable pointless unless we are able to control for endogeneity. One prime example of such a study was conducted by Levitt, who used the increase of police personnel in election year cycle to isolate the effect of police resources. Levitt found a negative correlation between police resources and crime. (Levitt, 1997)

The clear-up rate (also called clearance rate), on the other hand, is already by definition subject to the number of crimes in an area. If police resources are fixed in the short term, an increase in the number of crimes will lead to a drop in the clear-up rate. Eide refers to a framework by Fisher and Nagin, which models various types of sanctions and several different crimes to find that if one is to focus on a single crime category, the complementary and supplementary nature of different crimes make the relationship between the punishment and crime rate very complex (Fisher and Nagin 1978 via Eide 1994).

Past clearance rate is a very typical proxy for the likelihood of punishment. In reality, the link between actual clearance rate and individuals perception of the risk of getting caught could be influenced by factors such as visible police presence and media activity. Eide (1994) refers to studies in which people have been noticed to overestimate the average risk while underestimating their own risk of apprehension. Meanwhile Eide (1999) also finds that inmates' perception of risk of imprisonment corresponds closely to the actual rate. However, Eide refers to a study that uses interviews with inmates as the source of data and could thus be influenced by a bias as the respondents perception might have changed post-conviction. Furthermore the risk that criminals face is not that of getting caught but that of being convicted. To estimate the expected value of the cost for crime, an individual should possess information not only on his likelihood of getting caught but also the workings of the justice system and the level of punishment for that particular crime. For a more in-depth discussion on the perceived probability of punishment, see Sah (1991). The past clearance rate is nevertheless expected to have some effect on crime even if agents lack the knowledge of the effectiveness of police work since a higher rate of solved crimes indicates that more criminals are jailed.

Municipalities might be heterogeneous in the types of crimes committed and the implications for clear-up rate cannot be dismissed. Different crimes have differing clear-up rates and the overrepresentation of certain crimes might bias the general clear-up rate. In the case of shoplifting, for example, the clear up rate seems high because shoplifting is reported practically only in cases when the perpetrator is caught in the act. The clear-up rates for this particular crime are thus exaggerated by the data. (Virén, 2000) The problem is avoided altogether by using a per-crime clear-up rate instead of a measure calculated from aggregate figures. This is a more fine-grained approach in the sense that a per-crime clearance rate is expected to reflect not only police resources and the effectiveness of their use, but also the focal point of police work. The downside of this approach is a much larger volatility for the clearance rate of the more marginal crime categories.

Following the example of Eide (1994), the clearance rate I will use is an average of the three previous years. This smoothing is particularly useful in smaller municipalities, where volatility in clear up rates is high. Furthermore potential offenders might have a better understanding of the previous periods than the current one. The clear-up rates are treated on a per-crime basis. Precise data for conviction rates and the severity of punishments in Finland is not available on a municipal level. The clear-up rate thus serves as the sole deterrence variable in all of the regressions. This is a limitation for my empirical work if we assume that conviction rates and the severity of punishment differ between municipalities.

4.2.4 Socio-demographic variables

In the regressions I will employ the following socio-demographic control variables: population density, ethnic heterogeneity, amount of divorces, the proportion of young men in a population and the education index. While these factors are mainly seen as socio-economical ones, Bourguignon (1999) suggests that many of them may be closely related to labor market conditions.

Population density has repeatedly been found to correlate highly with criminal activity (see for example Eide, 1999). Ehrlich (1973) is among those authors that assume that the effectiveness of police work is highly dependent on population density. In addition to having a lower chance of getting caught, big cities tend to offer more criminal opportunities. Glaeser and Sacerdote estimate these two characteristics of high density areas to account for roughly half of the increase in crime that can be accounted by population density, while the remaining effect can be explained by tastes, social influences and family structure (Glaeser & Sacerdote, 1999). Cooter suggests that social norms work more efficiently in smaller communities and in groups where people frequently interact with each other. Also smaller communities have better means of informal punishment for a person deviating from commonly agreed upon rules. (Cooter, 1997) If we consider the concept of reputation cost beyond the criminal record, it is quite clear that the reputation cost both at the labor market and in a social context is larger in smaller communities.

The amount of ethnic heterogeneity is also controlled for in the regressions. Racial considerations are a key element in American studies, but race has also been found to play some part in crime in Sweden (Nilsson, 2004). Ethnic heterogeneity can be a proxy for, among other things, social cohesion. Similar grounds are often given for proxies that measure the mobility of residence or property ownership rates. In the following regressions, the variable for foreigners stands for the proportion of habitants that have a native language other than Finnish or Swedish.

Divorce rate has been found correlate very well with the crime rate (see for example Entorf and Spengler, 2002; Nilsson, 2004). The theoretical link between divorce rates and crime is not entirely clear. Levitt and Lochner (2001) name the quality of parenting as a key social factor determining crime. This would imply that broken families show up on crime rates with a sizable lag but it does not explain the more short-term effects that have been found empirically. Eide (1994) suggests that family problems and delinquency caused by same factors, such as poverty. I use the divorce rate per 1000 inhabitants as an explanatory variable in all of the regressions.

It is a well documented fact that a large share of crimes is committed by males of the age of 14-24 (see for example Entorf & Spengler, 2002). The explanations to why young men seem to be more prone to criminal acts are numerous. For one, young men have lower possibilities for legal income since their accumulated human capital is low (Lochner, 2004). If norm formation is assumed to be slow, then the norms of a person at a young age could differ from his or her norms at a later point in time. There is typically very little variation between different areas in the percentage of young males in the population. The proportion of young men in the Finnish population was not found to be relevant in Wahlroos's time-series analysis (Wahlroos, 1981). Their effect is nevertheless tested in the following regressions by the proportion of young males in a population.

Education is expected to affect criminal behavior in various ways. Schooling may affect earnings, the time available for crime as well as preferences. The relationship between education and measured crime on a macro level may also be affected by issues such as crime underreporting and the general moral in an area. The correlation between education and crime is expected to be negative through most of these channels. As education is linked with earnings potential, the theory expects the likelihood of offending to go down with an individual's educational level. In a micro level study by Lochner, crime was found to be "primarily a problem among young uneducated men" (Lochner, 1999). Similar results are found by Lochner and Moretti (2004). It has however also been suggested that individual skills might in some cases increase the rewards for crime and even the likelihood of offenses. A study by Levitt and Lochner suggest that males with high scores on mechanical information tests have an increased probability of committing crimes (Levitt & Lochner, 2001).

Another effect of education on crime is the time-availability argument, according to which youth busy with schoolwork simply have less time for criminal activity. Jacob and Lefgren (2003) use teacher training days as an instrument for school attendance. They find evidence that property crimes are significantly larger in areas where youth have more days off school. Jacob and Lefgren acknowledge that their results only imply short-term effects, but as Lochner and Moretti (2004) argue, the probability of committing crime could largely be state dependent and thus determined by past behavior. If this assumption is correct, allocating more time to school work could have long-lasting effects on crime reduction.

Machin et al. (2011) argue that education increases risk-aversity. If this is the case, then decreased risk taking is one explanation for the decreased likelihood that well educated individuals have for committing crimes. Education can likewise increase patience and thus make an agent less prone to short-sighted decisions such as participation in crime. Finally, schooling may directly alter preferences and make an individual more hesitant to breaking the law (Lochner & Moretti, 2004). Usher (1997) calls this the 'civilization effect' of education.

Although the reasons to expect education to reduce crime are numerous, the relationship between education and crime on a macro level is not as straightforward. Ehrlich found a positive and significant relationship between the level of education and criminal activity. He lists several theories that might explain this relationship, among them the possibility that higher average levels of education may be associated with less underreporting of crime. (Ehrlich, 1975, p. 333). Lochner also found a positive, although statistically insignificant, correlation between the rates for crimes such as forgery and counterfeiting, fraud, and embezzlement and average education levels. (Lochner, 2004). Lochners results might be explained by increasing returns to white collar crimes with skill level, as discussed above.

In the regressions that follow I use an educational index as a measure of the average educational attainment of a municipality. The percentage of 17 to 24 year olds without higher education is also tested as an alternative variable.

5 Empirical Results

This chapter contains empirical estimations of the effect between crime and inequality. The other explanatory variables used in the regressions were discussed in chapter 4. Chapter 5.1 offers a general description of the data. Chapter 5.2 summarizes the bivariate correlations coefficients between the explanatory variables used and crime rates as per crime category. These figures should be considered as description of the data and no definite conclusions should be made on their basis. A multivariate regression (OLS) will be conducted in chapter 5.3. A more complete model in chapter 5.4 will also take into account fixed effects between municipalities and periods. The fixed effects regression offers the best estimate for the effect that changes in inequality and other variables are expected to have on crime. The fixed effect regression is also conducted with various secondary instrument variables to ensure robustness. Chapter 5.5 will introduce dynamics to test for the persistence of criminal activity within a community. The dynamics will be incorporated through the use of an Arellano-Bond GMM model. Finally, in chapter 5.6 I offer a side-by-side comparison of all the results.

The OLS regression, fixed effects model and the GMM estimator are all techniques widely employed by criminometricians working with similar datasets. Although the methods differ significantly, the most robust findings will be present with all three models. We will see that in the case of the Gini coefficient and in particular theft crimes, all three methods yield similar results. However we are not able to draw definite conclusions about several of the control variables in cases where different models give differing results. This is the case with the percentage of young males, historical crime clear-up rate and the percentage of low income households.

5.1 Description of the data

The data set I use is a balanced panel series that covers the 337 Finnish municipalities according to municipality classifications from 2010. The smallest municipality in the group has as little as 115 inhabitants. The panel consists of annual figures from 1995 to 2009. In total this makes for 5040 observations. On an average year there were 432 000 reported crimes in Finland, out of which 280 000 were property crimes. A total of 2700 property crimes were not assigned to any municipalities and are thus omitted from the analysis. The amount of reported crime in Finland has been in a significant decline since the beginning of the 1990's (Figure 1). The population has grown seven percent between 1990 and 2010, while at the same time the number of property crimes reported is down by 35 percent.

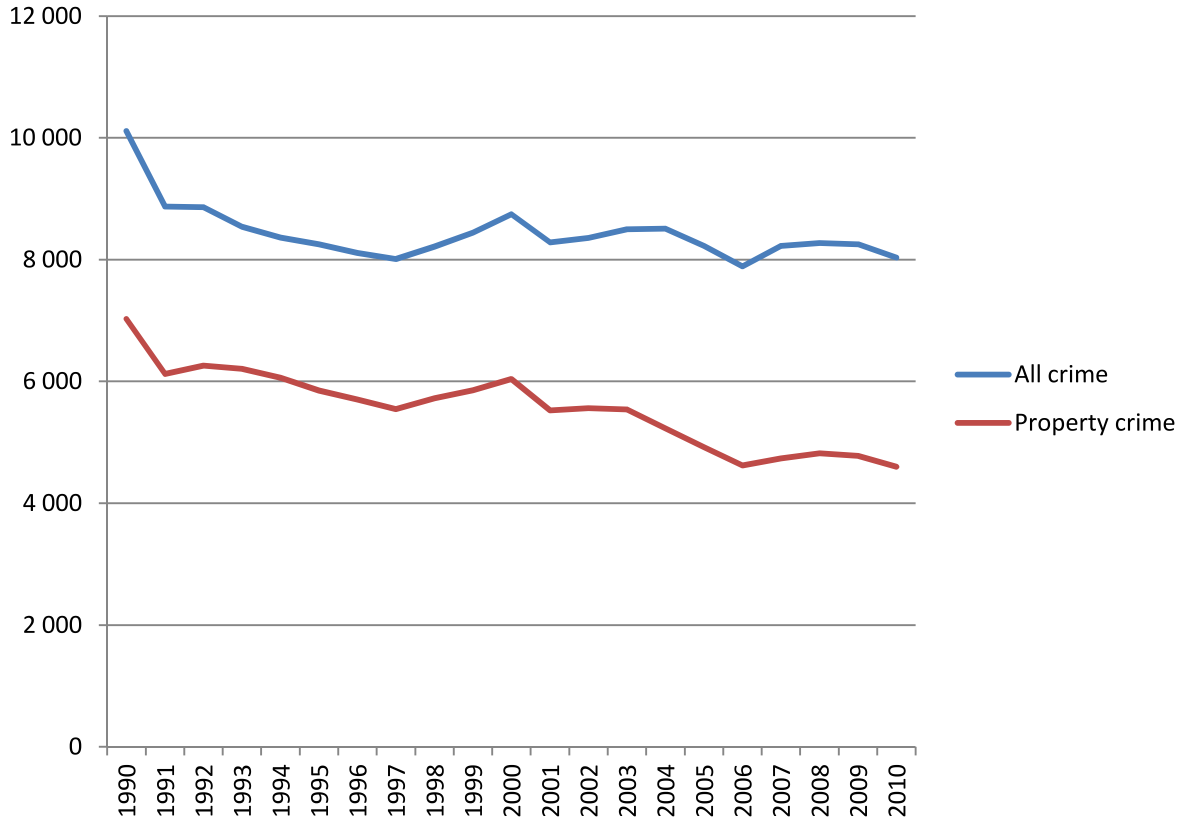

Figure 1 Reported crime in Finland 1990 – 2010, instances per 100 000 inhabitants

In 2010 the Finnish police authorities published crime statistics in a total of 14 major property crime categories and 50 subcategories. In part these subcategories are more detailed representation of the criminal act; for example theft from motor vehicles as a subcategory of total theft. Some categories are divided into two or three subcategories according to the severity of the act, such as theft, severe theft and petty theft. Several subcategories have been included only towards the end of the observation period and are thus not available for time series analysis. Large fluctuations within subcategories led to dismissing them from detailed analysis, as the stability of these classifications comes into question.

Within major crime categories, the crime rates have plummeted most for motor vehicle theft (-55 %) and robbery (-47 %). The reported cases for shoplifting, on the other hand, have risen by 102 per cent in the same time period. Shoplifting accounted for 22 per cent of all property crimes in 2010. This finding is likely not due to a boom in actual cases, but rather a change in the volume of reporting error. The prevalence in high reporting error and perhaps differing categorization between periods is also suggested by an extremely high level of volatility in categories such as tax fraud and smuggling.

The highest crime per capita (an average of 10 247 property crimes per 100 000 inhabitants per year) is found in the municipality of Helsinki. Most of the high-crime municipalities are urban areas. Maarianhamina, a municipality with only 10 000 inhabitants but the third highest crime rate per capita, makes a small exception. Part of the crime occurring on cruise ships between Finland shows up on the Maarianhamina statistics. The municipality will be omitted from the following empirical analysis. The distribution of the municipality level Gini coefficients and crime rates is seen in Figure 2.

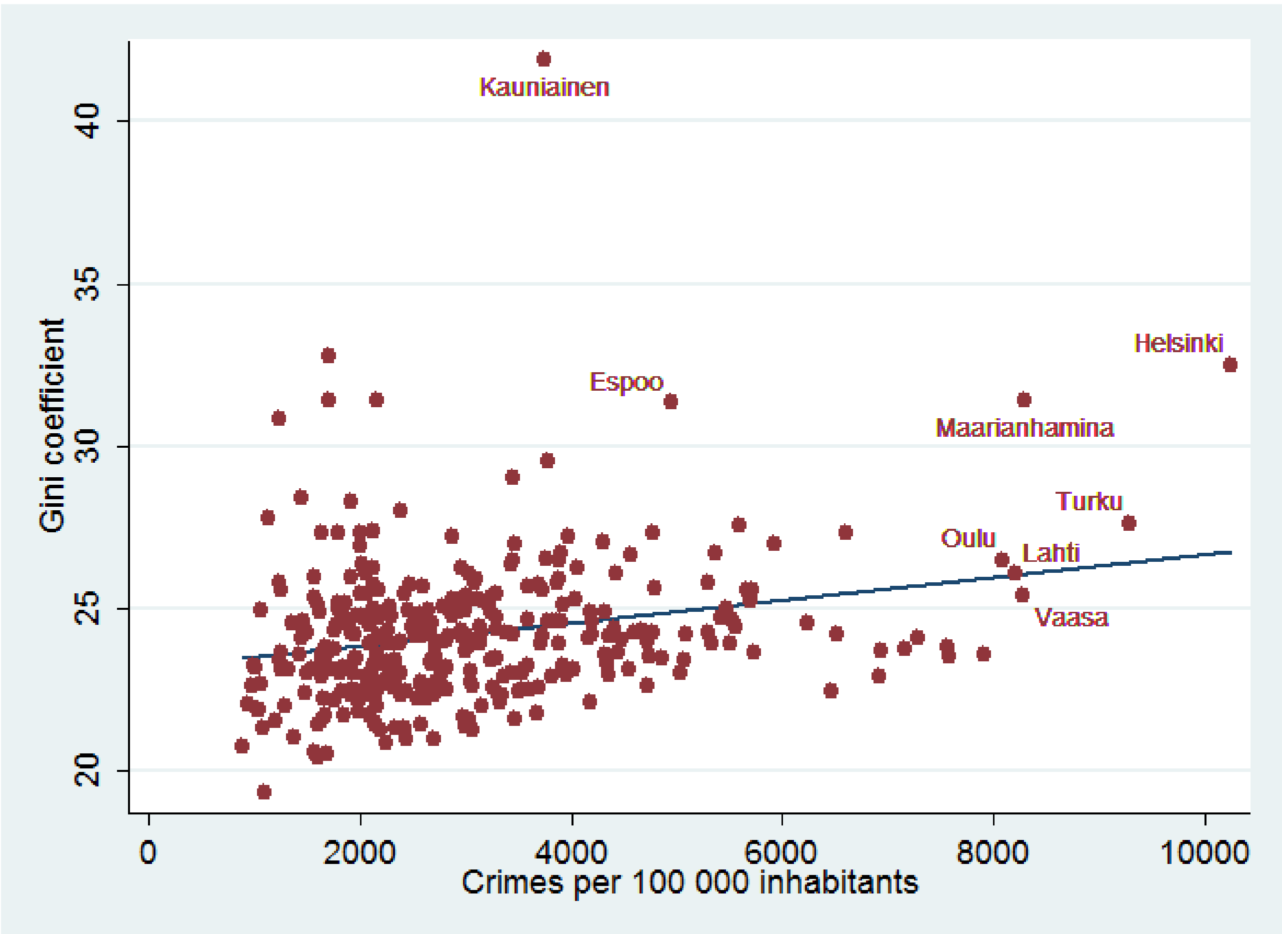

Figure 2 Average crime rates and Gini coefficients for Finnish municipalities 1995 - 2009

This paper uses a Gini coefficient for disposable income as a measure of income inequality. The per municipality income Gini coefficients are available from 1995 to 2009. During this timeframe the national Gini as well as the mean Gini coefficient have drifted upwards, as seen in Figure 3. The mean Gini coefficient among the Finnish municipalities was 24.2, with a standard deviation of 3.1. The average Gini coefficient of 41.8 in Kauniainen makes its income distribution the most unequal of all the municipalities in Finland. The lowest average Gini coefficient, 19.3, is found in Luoto.

Figure 3 The distribution of the Gini coefficient in Finnish municipalities 1995 - 2009

The data for this paper was collected through the electronic services of Statistics Finland and the National Institute for Health and Welfare's electronic database SOTKAnet. The original source for unemployment figures is the Ministry of Employment and the Economy. The welfare indicators are based on the research of the National Institute for Health and Welfare. The remaining figures are gathered by Statistics Finland. Table 1 summarizes the variables used in the regression models. For the OLS regression and the fixed effect model we study the first six crime categories listed in table Table 1. The remaining two - forgery and shoplifting - are included in the dynamic model to provide further points of comparison.

	Mean	Std. Dev	Min	Max
Crime rates (per 100 000)				
Violent crime	2464.6	2074.7	0.0	110918.4
Property crime	3052.9	1724.8	0.0	18741.5
Embezzlement	28.9	34.0	0.0	775.2
Fraud	132.9	238.2	0.0	8389.7
Robbery	13.6	30.2	0.0	1526.7
Theft	1780.9	1091.4	0.0	11433.9
Forgery	49.0	198.6	0.0	8186.7
Shoplifting	293.0	356.5	0.0	3103.7
Gini coefficient	24.2	3.1	15.9	66.1
Unemployment rate	12.8	5.7	0.0	33.9
Youth unemployment rate	16.7	9.4	0.0	54.5
Young males	2.6	0.6	0.0	5.3
Low income individuals	14.1	4.7	3.0	29.9
Population density	56.6	217.6	0.0	3034.0
Education index	208.2	47.6	110.0	543.0
*Without higher education *)*	12.2	4.1	0.0	60.0
Income / national average	0.9	0.1	0.7	1.6
Foreigners (per 1000)	11.4	27.8	0.0	500.0
Divorce rate	11.8	5.5	0.0	61.5
Clearance rate (3 year average) **)	35.1	12.0	0.0	150.0

Number of observations used: 5040

**) Only 4032 observations available*

***) Clearance rate calculated for all property crimes. The regressions use a per crime clearance rate.*

Table 1 Summary statistics

The inclusion of violent crime in the analysis is motivated by the fact that it makes for a very good point of comparison against property crimes and other studies. The economical motivations that play a part in property crime are nonexistent with violent crimes, whilst the psychological ones caused by inequality and other factors should have a similar effect.

Violent crime, in addition to aggregate property crime, is a typical categorization in existing literature. My results for these two categories may be compared to other studies, while for more defined crime types such comparisons are much harder to make.

5.2 Bivariate correlations

A positive correlation may be found between the Gini coefficient and the largest property crime categories as well as the aggregated crime rates. The simple two variable correlations are presented in Table 2 three different ways. The first row of figures represent correlation out of a pooled set of a total of 5040 observations. This approach treats all periods and municipalities equally. The second row contains the correlation coefficients of 15 year averages between the Gini coefficient and the crime rate. Such cross sectional analysis are not uncommon in criminometric studies, but this type of work lacks the very important intertemporal point of view. The third row, which contains correlations in the first differences captures the predicted effect of a change in one of the variables, but on the other but does not take into account possible differences in municipalities.

	Theft	Robbery	Fraud	Embezzlement	Property crime	All crime
All observations	.107	.071	.137	.070	.102	.144
15 year averages	.281	.169	.199	.308	.230	.162
First differences	.042	.009	-.002	.012	.026	.050

Table 2 Correlation between the Gini coefficient and different crime rates (log)

The strongest correlation between the Gini coefficient and crime rates can be found in long-run averages of the two variables. These figures might suggest that a large part of the variance in crime rates is explained by between-municipality differences that do not vary significantly between periods. The low first difference correlation is largely due to the fact that this method overlooks all variance between municipalities and the general trend in crime rates. The simple correlations overlook differences between areas that might affect the crime rate, the Gini coefficient or both.

This shallow analysis seems to suggest that a crime rates are higher in areas with relatively large inequality. A similar inspection may be made for the correlations between the crime rate and the explanatory variables that will be used in the following multivariate models. These figures are summarized in appendix A. Simple correlations reveal population density to be the variable most correlated with crime. The unexpected signs of the clearance rate, education index and poverty rate may be explained with a very high correlation with other explanatory variables. For example, the effect of high population density might overshadow the effect of poverty as large cities seem to have a smaller poverty rate yet a higher crime rate. The more refined models used in chapters 5.3-5.5 show that these results are not robust. The relationship between the crime rate and the regressors is easily misrepresented by choosing the wrong model.

5.3 Pooled OLS regression

In order to isolate the effect of inequality, we will next continue with a multivariate ordinary least squares (OLS) regression. National trends in crime are controlled for by yearly dummies in all the regressions, but omitted from the summary tables. The OLS approach assumes that all variance between municipalities that might affect crime rate is represented in the explanatory variables and that the error term is uncorrelated with crime rate. The assumptions of the OLS model are generally seen as too strict for similar scenarios. The possibility of omitted variable bias is treated in the next chapter with the fixed effects model. The regression results for six different crime classifications are summarized in Table 3.

	Theft	Robbery	Fraud	Embezzlement	Property crime	Violent crime
Gini coefficient	0.39	0.79	-0.15	0.54	0.158	0.006
	[4.94]**	[4.18]**	[1.15]	[3.71]**	[2.27]*	[0.09]
Population density	0.16	0.13	0.15	0.07	0.144	0.014
	[20.57]**	[7.66]**	[11.72]**	[5.23]**	[21.36]**	[2.04]*
Clearance rate (3 year average)	-0.07		0.08		-0.101	0.156
	[4.63]**		[2.90]**		[5.54]**	[8.56]**
Income / national average	0.1	0.17	0.01	-0.23	0.003	-0.021
	[1.86]	[1.35]	[0.15]	[2.30]*	[0.07]	[0.42]
Unemployment rate	0.28	0.12	0.28	0.02	0.257	0.201
	[13.17]**	[2.00]*	[6.93]**	[0.37]	[13.88]**	[10.88]**
Young males	-0.22	0.21	0.44	0.32	-0.061	0.075
	[6.54]**	[2.40]*	[7.57]**	[5.15]**	[2.08]*	[2.57]*
Low income	0.22	0.31	0.48	0.24	0.253	0.194
	[5.28]**	[3.27]**	[6.85]**	[3.27]**	[7.02]**	[5.40]**
Education index	0.61	-0.96	0.28	-0.38	0.581	0.125
	[8.42]**	[5.81]**	[2.25]*	[2.91]**	[9.09]**	[1.95]
Foreigners	0.18	0.11	0.11	0.15	0.168	0.112
	[16.93]**	[4.13]**	[6.26]**	[7.63]**	[18.15]**	[12.19]**
Divorce rate	0.19	-0.01	0.22	0.07	0.204	0.196
	[13.67]**	[0.23]	[8.98]**	[2.22]*	[16.57]**	[15.97]**
Observations	4768	2331	4213	3300	4783	4783
R-squared	0.48	0.12	0.26	0.11	0.51	0.32

Absolute value of t statistics in brackets. * significant at 5%; ** significant at 1%

Table 3 OLS regression results for various crime categories

Our main interest lies in the effect of Gini coefficient on crime. Inequality, as measured by the income Gini coefficient, seems to play very little part in determining fraud activity with the OLS model. Embezzlement, robbery and theft, on the other hand, seem quite highly correlated with the Gini. On an aggregate level, property crimes show a positive relationship to the Gini that is significant at the 5 per cent level. As all the variables are treated as logarithms, the coefficients listed above can be interpreted as elasticities. A one percent increase in the Gini coefficient is thus expected to have a 0.16 percent increase in property crime. The log-log transformation is also less sensitive to outliers which might otherwise cause a problem with the smallest municipalities in the data set.

For the more marginal crime categories, the low number of instances poses a significant statistical challenge. In the case of robberies for example, we omit a total of 2670 observations with zero events (1644 for embezzlement, 595 for fraud, and 17 for theft). The high number of observations with no criminal activity also reduces the explanatory power of the average clearance rate. In order to retain a high number of observations, the use of the clearance rate was abandoned for robbery and embezzlement. In all the regressions ran throughout the experiment, the past clearance rate of a municipality proved to be of very little significance.

5.4 Fixed effects model

Next we will use a fixed effect model to control for area specific differences. Controlling for fixed effects lets us work around the possibility that the regressors included in the model are not the only factors explaining differences in crime rates. In effect this approach assumes that there is a fixed amount of crime in each municipality that is caused by area specific characteristics not captured by the explanatory variables. A key assumption of the model is of course, that the area specific characteristics are stable between periods. The fixed effects approach is widely used by practitioners who work with similar data sets (see for example Levitt & Lochner, 2001; Nilsson, 2004). Results of the fixed effect regression are summarized in Table 4.

	Theft	**Robbery**	**Fraud**	**Embezzlement**	**Property crime**	**Violent crime**
Gini coefficient	0.28	-0.15	-0.29	-0.1	0.13	0.092
	[3.35]**	[0.59]	[1.44]	[0.47]	[1.84]	[1.30]
Population density	0.14	-0.6	-0.16	-0.16	-0.04	-0.007
	[2.09]*	[2.71]**	[0.97]	[0.98]	[0.71]	[0.12]
Clearance rate (3 year average)	-0.01		0.05		-0.056	0
	[0.84]		[1.97]*		[3.41]**	[0.02]
Income / national average	0.07	-0.34	-0.33	-0.56	-0.041	-0.022
	[0.35]	[0.64]	[0.74]	[1.31]	[0.25]	[0.13]
Unemployment rate	0.25	0.39	0.02	-0.11	0.154	-0.061
	[6.51]**	[2.82]**	[0.23]	[1.08]	[4.75]**	[1.86]
Young males	0.07	-0.05	0	0.1	0.106	0.003
	[1.86]	[0.36]	[0.04]	[0.95]	[3.25]**	[0.08]
Low income	0.01	-0.03	0.16	-0.01	0.077	-0.003
	[0.27]	[0.15]	[1.17]	[0.11]	[1.72]	[0.06]
Education index	-0.51	0.93	1.25	0.41	0.428	0.829
	[2.29]*	[1.31]	[2.29]*	[0.74]	[2.25]*	[4.33]**
Foreigners	0	0.12	0.11	0.07	0.024	0.014
	[0.23]	[2.22]*	[2.96]**	[1.78]	[1.90]	[1.08]
Divorce rate	-0.01	0.03	0	-0.02	-0.001	0.009
	[1.26]	[0.67]	[0.12]	[0.56]	[0.16]	[1.01]
Observations	4768	2331	4213	3300	4783	4783
R-squared	0.21	0.05	0.1	0.02	0.12	0.32

Absolute value of t statistics in brackets * significant at 5%; ** significant at 1%

Table 4 Fixed effects regression results for various crime categories

As was the case in the OLS regressions, the fixed effect model seems to be most suited for theft crimes. In this category the crime rate correlates well with the Gini coefficient, population density, unemployment rate and the education index. The finding is well in line with Choe (2008), who found burglary to be the crime category most correlated with the Gini coefficient (burglaries are included in the theft category in the Finnish data used in this paper). Kelly (2000) and Nilsson (2004) on the other hand, found opposite results. In their estimates the amount robberies rather than burglaries is most subject to inequality.

The model doesn't perform as well for robbery, embezzlement and fraud. For aggregate property crime, of which theft accounts for 60 per cent, the relationship between the Gini coefficient and property crime fails to exhibit statistical significance at the 5 per cent level. This is somewhat expected as the various components of property crime seem to have very differing coefficients for the regressors.

Most of the control variables prove to be less statistically significant once the municipality fixed effects are introduced in the model. In particular, the proportion of foreigners in a community, the divorce rate and the clearance rate present themselves as trivial for crime determination in a Finnish context. These three variables are however among the ones that have been found relevant in previous studies. The education index proved to have a differing effect on different types of crimes. Average schooling is negatively correlated with theft, but positively with fraud and especially violent crime. As discussed in chapter 4.2.4, it is possible that educational attainment for victims has an effect on the propensity to report crimes thus inflating the perceived crime rate. This is suggested by the fact that using the secondary variable for education (young individuals without higher education) practically eliminates the positive correlation for aggregate property crime and aggregate violent crime.

In an effort to ensure robustness of the fixed effects regression results, I tested the following secondary variables: youth unemployment instead of unemployment and young residents without higher education instead of the education index. Interestingly, the ratio of 17-24 year olds without higher education seems to be a more statistically significant variable than the average educational attainment of a certain area. However, this figure is available only from the year 1998 onwards. Preferring it over the education index would mean missing out on a substantial amount of observations. The differences between the youth unemployment rate and the general unemployment rate are negligible.

5.5 Dynamic panel data model

In this chapter I use a dynamic panel data GMM model to conduct a similar study than the one found in the previous chapter for the fixed effects model. The GMM model works under very different assumptions than the fixed effects model and thus provides good point of comparison. One purpose of this exercise is to verify whether the data supports the existence of criminal inertia and how they differ between crime categories. I employ an Arellano-Bond GMM (generalized method of moments) model which uses the crime rate lagged by one year as an explanatory variable. A similar approach is also used by, for example, Machin and Meghir (2004), Fajnzylber et al. (2002) and Bourguignon et al. (2003). Theoretical grounds for expecting dynamics to play an important part are strong. See chapter 2.5 for discussion on dynamics of crime.

The Arellano-Bond GMM estimator is designed for panels with few periods but a large number of units (small T, large N), such as this one. The model can also be used to address to endogeneity of explanatory variables. For example Kelly (2000) sees police activity as potentially endogenous. The same assumption could be made about most of the explanatory variables applied in this study. The regressions are run under the assumption that population density and the demographic variables are exogenous, while the Gini coefficient and other income related variables are predetermined, but not strictly endogenous. Clearance rate was first tested as an endogenously determined variable but ultimately dropped from the GMM regressions as its weak explanatory power might even weaken the model as a whole. The robustness of the model is tested at the end of this chapter by changing assumptions of endogeneity or omitting certain variables from the model altogether. The results of the GMM regressions are summarized in Table 5. Row 1 contains the coefficients for the lagged crime rate, which was found to be very different between crime types.

	Theft	Robbery	Fraud	Embezzlement	Property crime	Violent crime	Forgery	Shoplifting
Lagged crime rate	0.51	0.16	0.11	0.11	0.478	0.457	-0.005	0.287
	[32.88]**	[5.32]**	[5.43]**	[4.33]**	[29.84]**	[27.96]**	[0.18]	[13.55]**
Gini coefficient	0.32	0.56	-0.81	0.35	0.241	-0.069	-0.009	-0.576
	[4.18]**	[2.35]*	[4.75]**	[1.86]	[3.80]**	[1.08]	[0.03]	[3.71]**
Population density	0.11	0.16	0.11	0.1	0.102	-0.007	0.146	0.207
	[13.24]**	[7.03]**	[6.22]**	[5.43]**	[14.06]**	[1.04]	[5.30]**	[11.93]**
Income / national average	0.12	0.31	0.21	0.01	0.087	-0.024	0.177	0.03
	[2.05]*	[1.41]	[1.52]	[0.07]	[1.79]	[0.50]	[0.63]	[0.23]
Unemployment rate	0.21	0.41	0.12	0.2	0.213	0.088	0.338	0.296
	[12.32]**	[5.35]**	[2.75]**	[3.89]**	[15.01]**	[6.72]**	[3.89]**	[7.58]**
Young males	-0.03	0.23	0.25	0.33	0.011	0.023	0.721	0.303
	[1.03]	[2.29]*	[4.54]**	[4.83]**	[0.51]	[1.13]	[6.56]**	[5.74]**
Low income	-0.08	0.2	0.52	0.03	-0.032	0.21	0.063	0.431
	[2.98]**	[2.61]**	[8.26]**	[0.41]	[1.36]	[8.83]**	[0.62]	[7.16]**
Education index	-0.35	-0.41	0.79	-0.69	-0.176	0.442	-0.37	0.949
	[6.77]**	[2.27]*	[6.24]**	[5.03]**	[4.17]**	[10.11]**	[1.74]	[8.23]**
Foreigners	0.09	0.07	0.12	0.16	0.092	0.054	0.176	0.134
	[10.21]**	[2.13]*	[6.41]**	[7.31]**	[12.16]**	[7.65]**	[5.49]**	[7.92]**
Divorce rate	0.06	-0.06	0.11	0.02	0.072	0.064	0.068	0.193
	[5.51]**	[0.98]	[4.03]**	[0.44]	[7.34]**	[6.71]**	[1.23]	[7.58]**
Observations	4461	1545	3770	2496	4471	4471	2305	3697
Number of Countyid	330	229	320	292	331	331	283	317

Absolute value of z statistics in brackets * significant at 5%; ** significant at 1%

Table 5 GMM regression results for various crime categories

The regression results in Table 5 reveal that violent crimes, aggregate property crimes and especially theft crimes exhibit significant criminal inertia. Dynamics seem to play a smaller part in more skill-intensive crime categories such as robbery, fraud, embezzlement and forgery. Forgery is the only crime category tested where the lagged crime rate was not a statistically significant explanatory variable. Shoplifting is often seen as a crime motivated by peer influence rather than economic motives. However, it does not seem particularly subject to dynamics in comparison to other theft crimes.

Similar comparisons have also been made by other authors. Fajnzylber et al. (2002), find that homicides are more subject to criminal inertia than robberies - as does Choe (2008). Bourguignon (1999) finds the exact opposite to hold true. Choe's study compares different US states while the other two studies mentioned examine between-country differences. In line with columns 5 and 6 of Table 5, Choe finds property crime to be more correlated with the previous period crime than violent crime. However, Choe found the difference between the two crime types to be much larger. Machin and Meghir (2004), Neumayer (2005) and Nilsson (2004) also find significant persistence in property crimes. Their studies are not directly comparable to the results discussed here as they only focus on property crime on an aggregate level or work with differing classifications.

The relative complexity of the GMM model makes it sensitive to the assumptions made by the econometrician employing it. I tested the validity of my results with a simple robustness check, which is presented next. A standard issue of concern with GMM models is the use of too many instruments. I tested this possibility by running the same model for a different number of control variables. The smaller sets include only the variables that seem to exhibit the most statistical significance in the 9 instrument regression. Finally I test whether or not treating the Gini coefficient as an exogenously determined or, endogenously determined or predetermined but not strictly exogenous has an effect on the regression results. The endogenous Gini is instrumented with a lag of two periods while the predetermined but not strictly endogenous assumption is applied by instrumenting the Gini coefficient with a lag of one period. The coefficients for the Gini and the lagged crime rate for various alternative specifications are summarized in Table 6.

		Theft	**Robbery**	**Fraud**	**Embezzlement**	**Property**	**Violent**
Gini	**Predetermined gini**	0.32 [4.18]**	0.56 [2.35]*	-0.81 [4.75]**	0.35 [1.86]	0.24 [3.80]**	-0.07 [1.08]
	Endogenous gini	0.46 [4.69]**	0.91 [3.53]**	-1.24 [5.72]**	0.25 [1.13]	0.41 [5.01]**	-0.1 [1.22]
	Exogenous gini	0.41 [6.19]**	0.6 [3.14]**	-0.46 [3.23]**	0.71 [4.71]**	0.33 [6.03]**	0.05 [0.89]
	8 controls	0.33 [4.25]**	0.51 [2.12]*	-0.88 [5.06]**	0.25 [1.32]	0.26 [4.09]**	-0.09 [1.39]
	7 controls	0.18 [2.43]*	0.51 [2.16]*	-0.84 [4.82]**	0.16 [0.83]	0.12 [1.98]*	-0.03 [0.58]
	6 controls	0.24 [3.30]**	0.53 [2.21]*	-0.69 [3.96]**	0.23 [1.19]	0.18 [2.95]**	0.03 [0.41]
	5 controls	0.27 [3.69]**	0.59 [2.49]*	-0.67 [3.82]**	0.27 [1.38]	0.2 [3.20]**	0.03 [0.50]
	4 controls	0.31 [4.21]**	0.73 [2.94]**	-0.16 [0.86]	0.13 [0.65]	0.23 [3.86]**	0.31 [4.91]**
	3 controls	0.31 [4.21]**	0.73 [2.94]**	-0.16 [0.86]	0.13 [0.65]	0.23 [3.86]**	0.31 [4.91]**
	2 controls	0.11 [1.65]	0.32 [1.34]	0.82 [4.56]**	-0.28 [1.56]	0.3 [5.49]**	0.8 [12.26]**
	1 controls	0.13 [1.87]	0.01 [0.06]	0.54 [3.02]**	-0.4 [2.21]*	0.29 [4.96]**	0.78 [12.20]**
	0 controls	-0.04 [0.72]	-0.76 [3.91]**	0.83 [5.66]**	-0.61 [3.98]**	-0.06 [1.10]	0.72 [12.94]**
Lagged crime	**Predetermined gini**	0.51 [32.88]**	0.16 [5.32]**	0.11 [5.43]**	0.11 [4.33]**	0.48 [29.84]**	0.46 [27.96]**
	Endogenous gini	0.5 [31.77]**	0.15 [5.18]**	0.11 [5.16]**	0.11 [4.38]**	0.47 [29.35]**	0.45 [27.58]**
	Exogenous gini	0.48 [30.08]**	0.14 [4.64]**	0.11 [5.31]**	0.12 [4.58]**	0.45 [27.31]**	0.43 [25.67]**
	8 controls	0.5 [32.00]**	0.15 [4.94]**	0.1 [4.84]**	0.11 [4.13]**	0.47 [28.85]**	0.45 [27.08]**
	7 controls	0.56 [38.35]**	0.15 [4.88]**	0.11 [5.14]**	0.1 [3.94]**	0.54 [36.38]**	0.51 [33.43]**
	6 controls	0.58 [40.43]**	0.15 [4.95]**	0.12 [5.76]**	0.12 [4.45]**	0.58 [40.38]**	0.52 [34.10]**
	5 controls	0.58 [40.97]**	0.16 [5.06]**	0.11 [5.54]**	0.12 [4.56]**	0.58 [40.50]**	0.52 [34.12]**
	4 controls	0.55 [37.68]**	0.15 [4.62]**	0.14 [6.38]**	0.12 [4.24]**	0.53 [35.12]**	0.52 [33.71]**
	3 controls	0.55 [37.68]**	0.15 [4.62]**	0.14 [6.38]**	0.12 [4.24]**	0.53 [35.12]**	0.52 [33.71]**
	2 controls	0.53 [34.52]**	0.12 [3.60]**	0.19 [8.76]**	0.1 [3.51]**	0.48 [30.19]**	0.55 [36.21]**
	1 controls	0.62 [43.46]**	0.11 [3.13]**	0.15 [6.88]**	0.1 [3.48]**	0.58 [40.01]**	0.53 [34.47]**
	0 controls	0.58 [37.47]**	0.11 [2.98]**	0.14 [6.43]**	0.11 [3.72]**	0.49 [30.70]**	0.44 [26.19]**

*Absolute value of z statistics in brackets * significant at 5%; ** significant at 1%*

Table 6 Robustness test for the GMM model

Both of the coefficients listed in Table 6 seem to be quite insensitive when it comes to dropping variables from the original specification. The hypothesis that the full GMM specification used is suffering from too many instruments may be rejected. The degree to which the Gini coefficient is assumed to be exogenous does, however, have a notable effect on the magnitude of its correlation coefficient. Treating the Gini coefficient as completely endogenous typically increases its explanatory power. The model was also tested by changing assumptions of endogeneity for various control variables. This did not have a significant effect on the explanatory power of the Gini coefficient or the lagged crime rate.

5.6 Comparisons of the three regression models

The three models in the previous three chapters give somewhat differing results for the correlation coefficients. This chapter offers a side-by-side comparison and discussion about the overall results. All three models work under different assumptions, of which the OLS assumptions may be seen as the strictest and least likely to represent reality.

Any numerical goodness-of-fit tests would be misleading as the three models differ greatly. The predictive power of each model is illustrated by graphing out the predicted crime rate and the actual crime for each municipality for the year 2009. Figure 4 illustrates the differences between the three models for theft. A well performing model would produce a scatter plot where the observations lie within a relatively narrow diagonal line. We see that overall the GMM model offers good predictive power for theft (the same holds true for other crimes). This is well expected within the literature as the model uses lagged crime rate as one of the determinants of current crime rate.

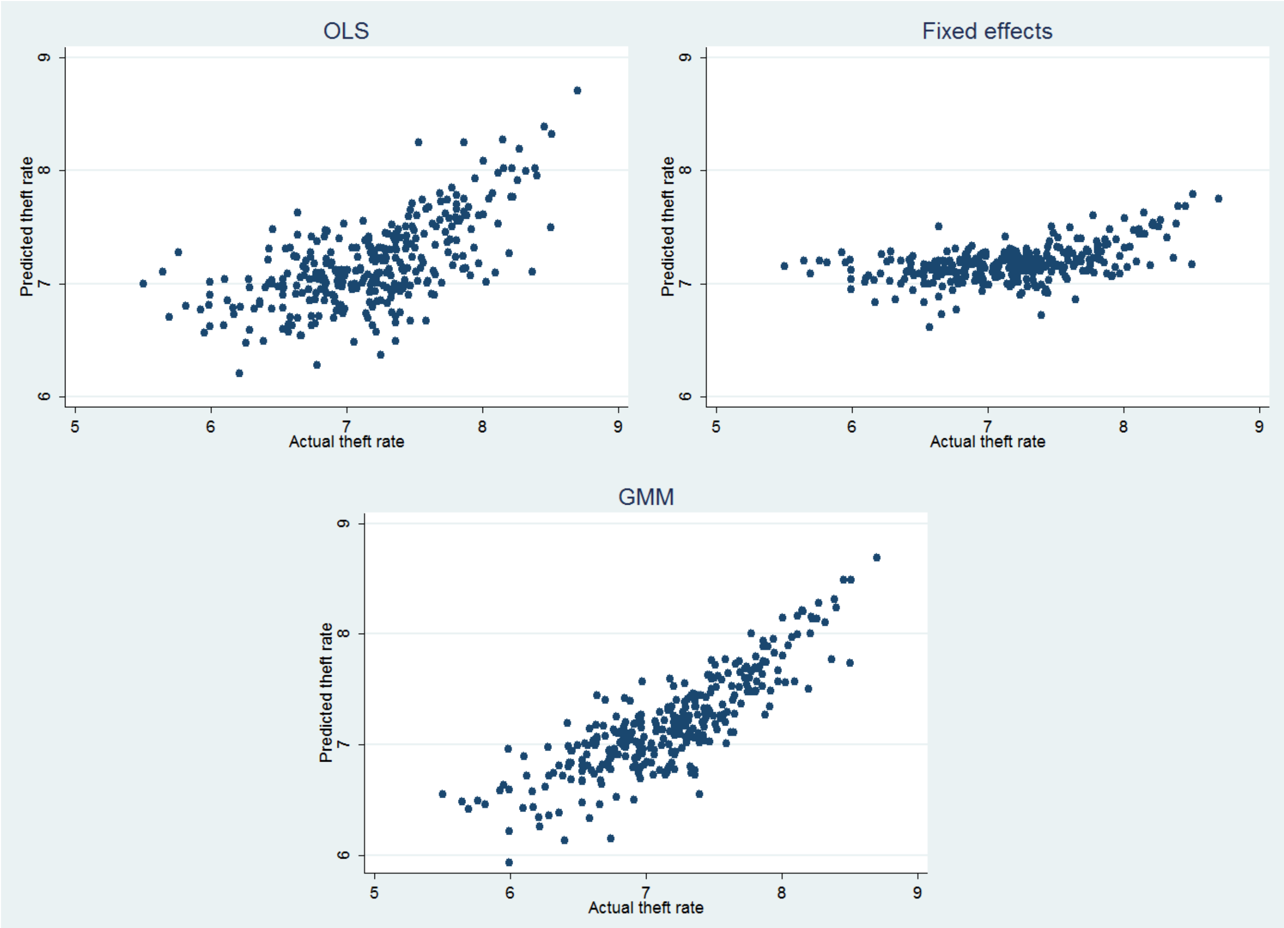

Figure 4 Predicted theft rates versus the actual theft rates, year 2009

As is evident in figure 4 and the following analysis, including fixed area effects in the model delivers results that differ greatly from the findings made with the pooled OLS model without fixed effects. The lack of a good fit for the fixed effects model may be explained by the fact that the model employs differences from the municipality mean. We must take into account the facts that first, yearly fluctuations in the Gini coefficient and other regressors are not large, and secondly that changes in said factors may have an effect on the crime rate with a lag that extends the one year period. Moreover, on the basis of the work of Dahlberg and Gustavsson (2008), we can expect that permanent rather than transitory income is the important factor in criminal decisions. Yearly changes in the Gini coefficient and other income variables partly represent temporary deviations from trends in permanent income; deviations which should not affect the crime rate.

Table 7Table 7 summarizes the regression results for theft, robbery and fraud while Table 8 offers a summary of embezzlement, aggregate property crime and violent crime.

	Theft			Robbery			Fraud		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
Lagged crime rate			0.51			0.16			0.11
			[32.88]**			[5.32]**			[5.43]**
Gini coefficient	0.39	0.28	0.32	0.79	-0.15	0.56	-0.15	-0.29	-0.81
	[4.94]**	[3.35]**	[4.18]**	[4.18]**	[0.59]	[2.35]*	[1.15]	[1.44]	[4.75]**
Population density	0.16	0.14	0.11	0.13	-0.6	0.16	0.15	-0.16	0.11
	[20.57]**	[2.09]*	[13.24]**	[7.66]**	[2.71]**	[7.03]**	[11.72]**	[0.97]	[6.22]**
Income / national average	0.1	0.07	0.12	0.17	-0.34	0.31	0.01	-0.33	0.21
	[1.86]	[0.35]	[2.05]*	[1.35]	[0.64]	[1.41]	[0.15]	[0.74]	[1.52]
Unemployment rate	0.28	0.25	0.21	0.12	0.39	0.41	0.28	0.02	0.12
	[13.17]**	[6.51]**	[12.32]**	[2.00]*	[2.82]**	[5.35]**	[6.93]**	[0.23]	[2.75]**
Young males	-0.22	0.07	-0.03	0.21	-0.05	0.23	0.44	0	0.25
	[6.54]**	[1.86]	[1.03]	[2.40]*	[0.36]	[2.29]*	[7.57]**	[0.04]	[4.54]**
Low income	0.22	0.01	-0.08	0.31	-0.03	0.2	0.48	0.16	0.52
	[5.28]**	[0.27]	[2.98]**	[3.27]**	[0.15]	[2.61]**	[6.85]**	[1.17]	[8.26]**
Education index	0.61	-0.51	-0.35	-0.96	0.93	-0.41	0.28	1.25	0.79
	[8.42]**	[2.29]*	[6.77]**	[5.81]**	[1.31]	[2.27]*	[2.25]*	[2.29]*	[6.24]**
Foreigners	0.18	0	0.09	0.11	0.12	0.07	0.11	0.11	0.12
	[16.93]**	[0.23]	[10.21]**	[4.13]**	[2.22]*	[2.13]*	[6.26]**	[2.96]**	[6.41]**
Divorce rate	0.19	-0.01	0.06	-0.01	0.03	-0.06	0.22	0	0.11
	[13.67]**	[1.26]	[5.51]**	[0.23]	[0.67]	[0.98]	[8.98]**	[0.12]	[4.03]**
Observations	4768	4768	4461	2331	2331	1545	4213	4213	3770
R-squared	0.48	0.21		0.12	0.05		0.26	0.1	

Table 7 Comparison of the regression results for theft, robbery and fraud

Results for theft are fairly constant regardless of the model. Our main focus is still on the Gini coefficient, which receives correlation coefficients in the range of 0.28 - 0.39. A rise in the Gini coefficient by the amount of the between municipality standard deviation (3.13) is thus expected to roughly correspond to a 3.6 % - 5.0 % rise in the theft rate. The difference between the Finnish municipalities with the highest and lowest Gini coefficients is 23, which implies a difference in theft rates due to the difference in inequality in the range of 26.6 % - 37.1 %. The one major exception of control variables for theft that is not consistent in all three models is the coefficient of the education index. The correlation between education and theft is estimated as positive by the OLS model and negative by the other two.

In the case of robbery we witness a reversal in the sign of several coefficients. While the OLS and GMM models offer somewhat similar predictions, the results from the fixed effects regression tells a very different story. While a positive relationship between inequality and robbery is suggested, definite conclusions cannot be made. For fraud we instead find that inequality and criminal activity is negatively correlated. This result is however not statistically significant except for the GMM model. Low income, education and the amount of foreigners seem to be the best and most consistent predictors for fraud. It is noteworthy that fraud activity and education exhibit a positive correlation. Credit card frauds and other payment frauds account for roughly half of the reported fraud cases in Finland.

	Embezzlement			Property crime			Violent crime		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
Lagged crime rate			0.11			0.478			0.457
			[4.33]**			[29.84]**			[27.96]**
Gini coefficient	0.54	-0.1	0.35	0.158	0.13	0.241	0.006	0.092	-0.069
	[3.71]**	[0.47]	[1.86]	[2.27]*	[1.84]	[3.80]**	[0.09]	[1.30]	[1.08]
Population density	0.07	-0.16	0.1	0.144	-0.04	0.102	0.014	-0.007	-0.007
	[5.23]**	[0.98]	[5.43]**	[21.36]**	[0.71]	[14.06]**	[2.04]*	[0.12]	[1.04]
Income / national average	-0.23	-0.56	0.01	0.003	-0.041	0.087	-0.021	-0.022	-0.024
	[2.30]*	[1.31]	[0.07]	[0.07]	[0.25]	[1.79]	[0.42]	[0.13]	[0.50]
Unemployment rate	0.02	-0.11	0.2	0.257	0.154	0.213	0.201	-0.061	0.088
	[0.37]	[1.08]	[3.89]**	[13.88]**	[4.75]**	[15.01]**	[10.88]**	[1.86]	[6.72]**
Young males	0.32	0.1	0.33	-0.061	0.106	0.011	0.075	0.003	0.023
	[5.15]**	[0.95]	[4.83]**	[2.08]*	[3.25]**	[0.51]	[2.57]*	[0.08]	[1.13]
Low income	0.24	-0.01	0.03	0.253	0.077	-0.032	0.194	-0.003	0.21
	[3.27]**	[0.11]	[0.41]	[7.02]**	[1.72]	[1.36]	[5.40]**	[0.06]	[8.83]**
Education index	-0.38	0.41	-0.69	0.581	0.428	-0.176	0.125	0.829	0.442
	[2.91]**	[0.74]	[5.03]**	[9.09]**	[2.25]*	[4.17]**	[1.95]	[4.33]**	[10.11]**
Foreigners	0.15	0.07	0.16	0.168	0.024	0.092	0.112	0.014	0.054
	[7.63]**	[1.78]	[7.31]**	[18.15]**	[1.90]	[12.16]**	[12.19]**	[1.08]	[7.65]**
Divorce rate	0.07	-0.02	0.02	0.204	-0.001	0.072	0.196	0.009	0.064
	[2.22]*	[0.56]	[0.44]	[16.57]**	[0.16]	[7.34]**	[15.97]**	[1.01]	[6.71]**
Observations	3300	3300	2496	4783	4783	4471	4783	4783	4471
R-squared	0.11	0.02		0.51	0.12		0.32	0.32	

Table 8 Comparison of the regression results for embezzlement, property crime and violent crime

For embezzlement the regressions fail to provide consistent results. While the OLS and GMM models offer very similar predictions on several regressors, the fixed effects model again makes contradicting predictions. The most likely culprit for the poor performance for robbery and embezzlement are the statistical problems of the more marginal crime categories discussed in chapter 5.3. The rate of these crimes in Finland is low enough to make the criminal acts seem sporadic with models that fare well with other crime categories.

For aggregate property crime the correlation coefficient is positive and fairly consistent. This result is all likelihood driven by theft crimes, which account for approximately 60 per cent of all property crimes. The single most consistent predictor of aggregate property crime is the unemployment rate. We cannot, however, expect the regression models to perform very well with the aggregate group as it is evident that the components that form the group have been shown to respond to the regressors in very different ways.

For violent crimes the estimated coefficient for inequality are very low and insignificant. While inequality and violent crime have been linked empirically by some authors, my findings are still in line with theory. Inequality is expected to increase criminal opportunities for property crime – an effect which is nonexistent for violent crime. Quite interestingly, the best predictors for violent crime seem to be the education index and the proportion of low income individuals – both of which have a positive effect on violent crime.

The clearance rate failed to display a statistically significant correlation with crime most categories. The only types of crime where the clearance rate showed a statistically significant effect were theft and aggregate property crime. This was the case whether or not we employ a per crime clearance rate or a clear up rate of all property crimes. Smoothing of the clearance was tested at various period lengths. None of these specifications made a significant impact on the explanatory power of the clearance rate. If the probability and severity of punishment does indeed vary significantly between periods and areas, the regression models used in this paper are made weaker by omitted variable bias.

6 Conclusions

I tested the empirical relationship between income inequality, as measured by the Gini coefficient, and crime rates in Finnish municipalities. The analysis was made for a data set spanning 337 municipalities and 15 years from 1995 to 2009. The models most suitable for this type of work seem to be a fixed effects model and a generalized method of moments (GMM) model. Using area specific fixed effects is a good way to avoid omitted variable bias that is likely to plague simple OLS regressions. Introducing fixed effects changes the correlation coefficients drastically and reduces the apparent correlation between the Gini coefficient and crime rates. The fixed effects model fails to find a statistically significant relationship between the Gini coefficient and crime rates with the exception of theft crimes.

The GMM method on the other hand finds a more statistically significant relationship between the gini and property crime rates. This method takes into account dynamics and endogeneity of regressors. Both issues seem to be highly relevant when studying crime rates. If criminal activity does indeed persist over periods, it is possible that the coefficients in static models are underestimated. Criminal inertia suggests that a change in any of the coefficients would continue to have an effect for several periods. The time-span of static models might thus prove to be too short to properly represent reality. These issues may be reflected in the trend witnessed in more recent studies of favoring the GMM model.

As is the case in existing literature, findings between my different specifications are somewhat contradictory. The key question of correlation between inequality and crime was found to be positive and statistically significant for theft crimes. For robbery crimes and property crimes in general, the evidence is weaker as the fixed effects model does not find a statistically significant relationship. The GMM results suggest that robbery crimes be the ones most directly affected by inequality and income opportunity variables such as unemployment. The direct effect for theft crimes seem to be somewhat lower, but persist longer due to the highly dynamic nature of theft. The very high multiplier effect for theft crimes suggest that in the long term, theft rates are the ones that are most subject to shocks to inequality, unemployment, education and population density.

For violent crimes the Gini coefficient was found to be irrelevant in determining crime rates. The evident difference between property crimes and violent crimes suggests that inequality may act as a catalyst for crime mostly because of increased opportunities for property crimes. The finding doesn't support theories which link inequality and criminal activity through psychological motivation.

Several control variables that were expected to be of great importance proved out to be insignificant in many of the regressions ran throughout this study. These include the clear-up rate of crimes, divorce rate, and the percentage of young males in an area. With these variables it is hard to argue that long term levels rather than yearly changes might dictate changes in the crime rate. The relationship between education and crime is complex in light of theoretical consideration as well as the results of my empirical work. The general education index was found to be negatively correlated with some crimes but positively correlated with, for instance, violent crime. One explanation for this is a possible correlation between education of victims and the underreporting rate of crimes. The ratio of non-educated youth was however a clearly positively correlated predictor of crime rates.

On the basis of my empirical work, clear distinctions may be made between different types of crimes. My findings suggest that crimes such as fraud and embezzlement are largely driven by other factors than theft and robbery. In the Finnish setting over 60 per cent of reported property crimes are accounted by for theft crimes. Fluctuations in the general property crime rates thus reflect in large part changes in the number of thefts - mainly petty theft. My findings suggest that future examination of the topic should be made on a per-crime basis rather than investigating property crimes as a whole.

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APPENDIX A: Pairwise correlations of the various sociodemographic variables and the property crime rate in Finnish municipalities, 1995-2009

	Property crime	Population density	Clearance rate (3 year avg.) 1)	Income / national average	Unemployment rate	Young males	Low income individuals	Education index	Foreigners (per 1000)	Divorce rate
Property crime	1									
Population density	0.55*	1								
Clearance rate (3 year average) 1)	-0.06*	-0.11*	1							
Income / national average	0.02	0.08*	-0.06*	1						
Unemployment rate	0.14*	-0.19*	0.31*	-0.04*	1					
Young males	0.19*	0.30*	0.19*	-0.04*	0.17*	1				
Low income individuals	-0.21*	-0.52*	0.27*	-0.04*	0.25*	-0.15*	1			
Education index	0.31*	0.58*	0.04*	0.01	-0.34*	0.20*	-0.24*	1		
Foreigners (per 1000)	0.35*	0.47*	-0.13*	-0.01	-0.35*	0.03*	-0.08*	0.54*	1	
Divorce rate	0.42*	0.36*	0.01	0.02	-0.03*	0.05*	-0.10*	0.32*	0.30*	1

** significant at 5%*

1) Clearance rate calculated for all property crimes. The regressions use a per crime clearance rate.