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# Social Interactions and Crime Revisited: An Investigation Using Individual Offender Data in Dutch Neighborhoods

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# **Social Interactions and Crime Revisited: An Investigation Using Individual Offender Data in Dutch Neighborhoods\***

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## **Abstract**

Using data on the age, sex, ethnicity and criminal involvement of 14.3 million residents aged 10–89 residing in 4,007 neighborhoods in the Netherlands, this article tests whether an individual's decision whether or not to be involved in crime is affected by the number of criminals in the neighborhood. Controlling for unobserved neighborhood heterogeneity and endogeneity of this decision, a small positive effect is found on violent crime, but not on property crime. The results suggest that individual characteristics and other neighborhood characteristics play a much greater role in an individual's decision to be involved in crime.

**Keywords:** social interactions, neighborhoods, crime

**JEL-classification:** R1, R2

# 1. Introduction

The geographic variability of crime is a longstanding puzzle that was already studied in the early 19th century by statisticians Quetelet (see Beirne, 1987) and Guerry (see Friendly, 2007). A seminal paper on the topic (Glaeser et al., 1996, GSS hereafter) analyzes data on 658 cities in the United States and 70 precincts in New York City. Their findings demonstrate that for a variety of crime types, the variability in crime rates cannot be explained by economic, social or legal differences between cities or precincts. The authors conclude that the remaining variability should be attributed to ‘social interactions’, a term that encompasses a variety of different nonmarket mechanisms but is seldom explicitly defined (Manski, 2000). A common theme is the proposition that the optimal choice of an individual depends on the choices of others, in particular others with whom the individual interacts directly or vicariously. If people interact predominantly with others who are geographically nearby, these interactions may provide an alternative explanation for the geographical variability of crime.<sup>1</sup>

The present paper builds on the argumentation of GSS, but utilizes data that are better suited to gauge the effect of social interactions on an individual’s criminal behavior in three important ways. First, our analysis utilizes data measured at a much smaller spatial scale. Whereas GSS apply their model to cities and to precincts as spatial units of analysis, we use Dutch neighborhoods that have an average population of 4,000 residents and an average surface of 10 square kilometer (approximately 4 square miles). The detailed spatial scale is not only important for statistical reasons (e.g., it assures less heterogeneity within and more heterogeneity between observations) but also from a substantive point of view. In order for the choices of individuals to be affected by the

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<sup>1</sup>See, for instance, Case and Katz (1991), Freeman et al. (1996) and Zenou (2003) and the references cited in these papers for further empirical evidence, Ballester et al. (2010) for a theoretical analysis of delinquent networks in the tradition of Becker (1968) and Calvo-Armengol and Zenou (2004) for the presence of multiple equilibriums.

choices of others in their environment, they must be aware of these choices. Given the limited spatial awareness of individuals, they are much more likely to be aware of the behaviors of the residents in their own neighborhood than of the behaviors of residents in remote parts of their city or region.

Second, our analysis directly applies to individual choices. GSS have only access to crime rates, i.e. annual numbers of crimes per capita committed within the geographic boundaries of cities or precincts. This requires them to make assumptions on the numbers of crimes committed per criminal. Our data apply to individual neighborhood residents, which allows us to analyze offender rates (percentages of neighborhood residents suspected of being involved in crime in a given year) rather than crime rates. This allows us to separate crimes from offenders, i.e. choices from agents.

The third advantage of our study is the inclusion of individual characteristics (sex, age and ethnic origin) that are strongly correlated with criminal involvement. In contrast to GSS, who rely on aggregate population characteristics, we analyze individual data that are both comprehensive and detailed. This allows us to take into account stylized facts about individual determinants of criminal conduct, such as the overrepresentation of males, adolescents and non-native residents among the criminal population. Our analysis includes the age (16 categories), sex (male versus female), ethnic origin (native versus foreign), neighborhood of residence (4,000 neighborhoods) and criminal record of the complete registered 2006 population aged 10–89 of The Netherlands. The sample totals 14.3 million residents of whom just over 21,300 were registered for being suspected by the police of having committed a crime in 2006. As far as we know no prior study has been based on such a large dataset of individual records.

Our empirical work is based on a binomial choice model of the individual's choice of whether or not to be a criminal. Explanatory variables include individual as well as neighborhood characteristics. The fraction of criminals in the neighborhood is included

in the latter group. Identification of endogenous social interactions is complicated by the ‘reflection problem’ Manski (1993). Brock and Durlauf (2001) provide a set of conditions under which such social interactions are identified in binomial discrete choice models. To address unobserved heterogeneity, which could bias the measurement of social interactions, we employ the methodology of Berry et al. (1995). In addition, we tackle the endogeneity of a possible social interaction effect with an artificial instrumental variable.

The remainder of this paper is structured as follows. The next section discusses the economic and criminological literature on crime and social interactions. Section 3 addresses the model and the estimation methodology. Section 4 extensively describes the data used. Section 5 presents the findings, after which the final section concludes and provides suggestions for future research.

## 2. Literature

As GSS argue, high geographic variability of crime rates implies that the behavior of two people living in the same geographic area is on average more similar than the behavior of two people living in different geographic areas. Manski (1993) distinguishes between three mechanisms that can create behavioral similarity in groups. The first mechanism is endogenous interaction, in which the propensity of an individual to behave in some way (e.g., commit crime) varies with the behavior of the group (e.g., the proportion of group members that are criminals). The second mechanism is exogenous or contextual interaction, in which the propensity of an individual to behave in some way varies with exogenous characteristics of the group members (e.g., age and gender composition). The third mechanism is correlated effects, in which individuals in the same group behave similarly only because they have similar unobserved individual characteristics or face similar unobserved constraints (in our case these are unobserved

neighborhood characteristics influencing crime rates). Correlated effects represent a non-causal mechanism, even if group membership (e.g., living in the same neighborhood) is caused by self-selection on exogenous characteristics (e.g. affluence or race).

In contrast to correlated effects, endogenous and contextual interactions are causal effects. Manski notes that interest in both types of interactions marks a disciplinary divide: whereas sociology has emphasized contextual interactions, the interest of economics has been primarily in the behavioral interdependence and feedback loops implied by endogenous interactions. Endogenous interaction generates a multiplier effect on the impact of other explanatory variables on the probability of choosing to be a criminal. This multiplier effect is at the heart of the necessity of introducing social interactions to explain the geographical variation of crime rates.

In criminological research, it has long been observed that peer delinquency and individual delinquency are correlated, i.e. that those who break the law tend to associate with others who also break the law, although empirically the proposition is tested almost exclusively amongst juveniles, not adults. Two mechanisms have been hypothesized to underlie that correlation. The first mechanism is social learning (Sutherland, 1947; Akers, 1985), according to which criminal behavior is learned from delinquent peers. People are more likely to commit crime if peers also commit crime and learning includes being taught the tangible techniques of committing crime, but also learning cognitive techniques of neutralization to overcome moral concerns (Sykes and Matza, 1957). This mechanism is an example of both contextual interaction with regard to learning specific skills, but also endogenous interaction because it implies behavioral interdependence.

The second mechanism is group selection. According to this argument, criminality itself is caused by other factors (such as weak social bonds or low self-control, see Gottfredson and Hirschi, 1990), and the propensity of an individual to be a criminal is not caused by the company of criminal friends. Instead, causality runs the other way: criminals tend to



seek the company of other criminals. Because association is also based on geographical proximity (Festinger et al., 1950), peer group or neighborhood selection induces behavioral similarity in criminality. This mechanism is an example of correlated effects, and not driven by behavioral independence with respect to the decision to become a criminal.

The correlation between peer delinquency and individual delinquency is thus hypothesized to be affected by processes of selection and influence in social interactions between peers. In one of the first criminological studies to employ longitudinal network analyses to study the causal ordering of selection and influence, Weerman (2011) shows that only the average delinquency level of someone's friends in the school network has a significant, although relatively small, effect on individual delinquent behavior. Patacchini and Zenou (2012) also study delinquency in peer networks and find a 'conformism' effect of peers' delinquency for all crimes but especially for petty crimes.

Social influence thus seems to be most important to explain the correlation between peer delinquency and individual delinquency. Measuring the full extent of social networks to identify and estimate social interactions may, however, be unnecessary restrictive, because social interactions are likely to play a role not only in networks of strong ties, but also in networks of weak ties. Social interactions include mechanisms that do not rely on the identification of other individuals. For example, an individual's decision to commit crime may be affected by merely observing the behavior of unknown others, or even by just observing the outcomes of it (e.g., vandalism), and inferring the behavior.

In this paper, we focus on the endogenous interactions between neighborhood residents, and test the hypothesis that, all other things being equal, an individual's decision to be a criminal positively depends on the proportion of neighborhood residents that are criminals. Thus, we expect that one's behavior is influenced by observing or learning about the behavior of other neighborhood residents. Relevant examples for the purposes of this paper are *(i)* see crime take place, *(ii)* hear about crime taking place from offenders

and/or victims in one's peer group, *(iii)* see the results of crime, and *(iv)* become a victim of crime.

A focus on the neighborhood as the presumed unit of analysis where individuals interact with each other seems logical, given the wealth of published research on neighborhood effects (for an overview of outcomes unrelated to crime, see Sampson et al., 2002). As Shaw and McKay (1969) pointed out in their highly influential work: "Heavy concentration of delinquency in certain areas means [...] that boys living in these areas are in contact not only with individuals who engage in proscribed activity but also with groups which sanction such behavior and exert pressure upon their members to conform to group standards" (p. 174). The neighborhood is an important context for studying the role of social interactions in crime, not only for adolescent boys, as the above quote suggests, but for neighborhood residents of both sexes and all ages.

We analyse property crime and violent crime separately as well as jointly in an overall measure that includes both types of crime. The rationale is that if criminal social interactions exist, they may be crime type specific. This would imply that an individual's decision to become involved in property crime depends on the proportion of property offenders (but not on the proportion of offenders of a different type of crime) in his or her environment, and that the probability to become involved in violent crime depends on the proportion of violent offenders (but not on the proportion of other types of offenders) in the area. Violent crime includes offences like assault, domestic violence and robbery. Property crime includes offences like burglary, shoplifting and fraud. Because violent crime has a strong reciprocal nature (assault often takes place for reasons of revenge, and the perpetrators of assault are often identified while those of property crime often are not), we hypothesize that the social interaction effect for violent crime is larger than for property crime.

### 3. The Model

This section presents the model and the method of estimation. We use a binomial logit model for the choice whether or not to be a criminal. This choice is determined by personal characteristics as well as neighborhood characteristics. Idiosyncratic differences in individual choice behavior are captured by the conventional logit error term. We also address unobserved neighborhood effects, by introducing elements of the approach pioneered by Berry et al. (1995) along the lines of Walker et al. (2011) in their model of social interactions in travel mode choice. Subsequently, we deal with the issue of correct identification of the social interaction effect, and we address the endogeneity of the social interaction effect. The final subsection discusses an implication of our model: the existence of multiple neighborhood crime rate equilibriums.

#### 3.1. The choice of whether or not to be a criminal

The model we use focuses on the an individual's choice of whether or not to be a criminal. An individual decides to either be a criminal or not. The choice depends on personal and neighborhood characteristics, not all of which are observed. Let  $C_{ij}$  be a zero-one variable that indicates whether individual  $i$  in neighborhood  $j$  is a criminal. The probability that  $C_{ij}$  equals 1 (indicating that person  $i$  is a criminal) depends on personal characteristics  $X_i$ , and on neighborhood characteristics  $Z_j$ . A social interaction effect is present if the expected value of the variable  $C_j$  in neighborhood  $j$  has an impact on the probability that a particular individual  $i$  chooses to be a criminal. Since we are not informed about all the relevant characteristics, we introduce two random variables representing unobserved characteristics:  $\epsilon_i$  for unobserved personal characteristics and  $\xi_j$  for unobserved neighborhood characteristics. We now define a latent variable  $y_{ij}$  that is

linear in these characteristics:

$$y_{ij} = \alpha X_{ij} + \beta Z_j + \gamma E(C_j) + \xi_j + \epsilon_{ij}. \quad (1)$$

When this latent variable takes on a positive value,  $C_{ij} = 1$ , otherwise  $C_{ij} = 0$ .

If we assume the random variable  $\epsilon_i$  to be extreme value type I distributed the probability that  $C_{ij} = 1$  is given by the logit expression:

$$\Pr(C_{ij} = 1) = \frac{e^{\alpha X_i + \beta Z_j + \gamma E(C_j) + \xi_j}}{1 + e^{\alpha X_i + \beta Z_j + \gamma E(C_j) + \xi_j}}. \quad (2)$$

Without the social interaction and unobserved neighborhood effects (i.e.,  $\gamma = \xi_j = 0$ ), this is a standard binomial logit model. When there is social interaction, but no unobserved heterogeneity ( $\xi_j = 0$ ), this is the logit version of the binomial model of Brock and Durlauf (2001).

The unobserved heterogeneity term  $\xi_j$  captures neighbourhood characteristics that may have an impact on an individual's probability to become a criminal, but are unobserved by the analyst. The importance of such unobserved heterogeneity in discrete choice models is analyzed thoroughly by Berry et al. (1995) in their seminal study of the automobile market. Their approach is used in other fields as well. For instance, Walker et al. (2011) apply a model like (2), but without neighborhood variables  $Z$ , to study the effect of social interactions on travel mode choice.

### 3.2. Identification

Berry et al. (1995) suggest a two-stage procedure. In the first step the neighborhood-specific terms are taken together in a single neighborhood constant  $\delta_j$ .

$$\Pr(C_{ij} = 1) = \frac{e^{\alpha X_i + \delta_j}}{1 + e^{\alpha X_i + \delta_j}}, \quad (3)$$

and this model is estimated in the usual way. In the second stage the alternative specific constants are analyzed further by writing them again as:

$$\delta_j = \beta Z_j + \gamma E(C_j) + \xi_j. \quad (4)$$

The unobserved heterogeneity terms  $\xi_j$  are now the residuals of the linear regression equation. A complication is that OLS cannot be used, since  $E(C_j)$  is expected to be correlated with  $\xi_j$ . The reason is that a high value of  $\xi_j$  makes it more likely that any individual in the neighborhood is a criminal, which tends to increase  $E(C_j)$ . Hence the error term is not independent of the explanatory variables. In the next subsection we will propose a solution to this problem using an instrumental variable approach.

Manski (1993) studies identification of a linear model with social interactions in which there are endogenous interaction effects as well as contextual effects. In our model the variable  $E(C_j)$  embodies an endogenous social interaction effect, while contextual effects may be included in the vector  $Z_j$  when it contains variables like the average age of neighborhood inhabitants. In Manski's model, the two effects cannot be distinguished. Brock and Durlauf (2001) show that the nonlinearity that occurs in a discrete choice model like (2) has identifying power. They develop a set of conditions under which all the remaining parameters are identified. These conditions apply to the model (2) when the term referring to unobserved heterogeneity is absent.

The model (2) is identified if the parameters  $\alpha$  and  $\delta$  in (3) are identified and if the parameters  $\beta$  and  $\gamma$  in (4) are identified. Manski (1988) shows that the multinomial logit model is identified, so the first requirement is not a problem. Nor is the second. In Manski’s linear model  $C_{ij}$  is on the left-hand side of the linear equation of interest, whereas in (4) it is the estimated neighborhood-specific constant  $\delta_j$ . This is the reason why Manski’s reflection problem does not occur in the present context.

However, there is another problem that has to be faced: the term  $\xi_j$ , which represents unobserved heterogeneity, has an impact on all  $C_{ij}$ ’s and therefore also on  $E(C_j)$ . The implication is that  $E(C_j)$  is potentially correlated with  $\xi_j$ . In the next subsection we will propose an instrumental variable strategy to solve this problem.

### 3.3. Endogeneity

As an instrument we need additional variables that have no direct impact on  $\delta_j$ , and are correlated with  $E(C_j)$ , but not with  $\xi_j$ . Walker et al. (2011) propose two types of instruments: a spatial reference group, or the average social interaction effect of the adjacent postal codes; a social reference group, variables that indicate whether inhabitants of a neighborhood share similar socio-economic characteristics.

The intuition behind this approach is straightforward.  $E(C_j)$  is defined as the expected number of criminals within a neighborhood. This can also be seen as the probability to encounter a criminal within neighborhood  $j$ . Note that one of the main assumptions of our model is that social interactions take place within a neighborhood. Thus, spatially lagged encounter probabilities  $WE(C_j)$  are not correlated with the neighborhood specific effect, but might contain information about  $E(C_j)$ . Similarly, the social distance in the neighborhood to other groups should be correlated with  $E(C_j)$  (it contains information about the strength of the network and thus the intensity of the social interactions)

and the correlation with the unobserved neighborhood characteristics is expected to be rather weak. For instance, it can be argued that it is unlikely that a neighborhood's age structure correlates with the propensity of becoming a criminal other than via group interactions.

However, these approaches are easy to criticize. It is not difficult to imagine social interactions that cross the often somewhat arbitrary boundaries of zip code areas, which would violate the exclusion restriction. It is also quite conceivable that the demographic composition of a neighborhood has a direct impact on the probability that some of its inhabitants become criminals. Given this criticism, it is advantageous that Bayer et al. (2004) developed a procedure for constructing an instrument in the context of a model for neighborhood sorting. We follow their suggestion here.

Start by observing that, according to the model, the expected crime rate is:

$$E(C_j) = \left( \sum_{i \in j} \frac{e^{\alpha X_i + \beta Z_j + \gamma E(C_j) + \xi_j}}{1 + e^{\alpha X_i + \beta Z_j + \gamma E(C_j) + \xi_j}} \right) / B_j, \quad (5)$$

where the summation is over all individuals living in neighborhood  $j$  and  $B_j$  is the total number of these individuals. This equation must necessarily hold if the model is consistent and can be interpreted as an equilibrium condition in our model of social interaction. It is easy to verify that in (5) there is a positive correlation between the unobserved neighborhood characteristics and the crime rate.

If we know the true values of the coefficients  $\alpha, \beta, \gamma$  and the unobserved neighborhood characteristics  $\xi_j$  we would be able to compute counterfactual choice probabilities, denoted as  $IE(C_j)$ 's, for the situation in which unobserved neighborhood effects were absent, that is for a situation in which all  $\xi_j$ 's are equal to 0. The  $IE(C_j)$ 's are, by construction, uncorrelated with the  $\xi_j$ 's and in all probability highly correlated with the  $E(C_j)$ 's. Since the exclusion restriction is also clearly satisfied, this constructed variable could serve as

an instrument.

The instrument is thus computed by deleting the unobserved heterogeneity terms  $\xi$  from (5) and computing the expected crime rate implied by the resulting equation:

$$IE(C_j) = \left( \sum_{i \in j} \frac{e^{\alpha X_i + \beta Z_j + \gamma IE(C_j)}}{1 + e^{\alpha X_i + \beta Z_j + \gamma IE(C_j)}} \right) / B_j. \quad (6)$$

A complication associated with implementing the suggested procedure is that (6) uses the estimated coefficients of the model, which can only be obtained through the use of the instrument. Bayer et al. (2004) and Bayer and Timmins (2007) therefore propose an iterative procedure in which one starts with an informed guess of the instrument values,<sup>2</sup> then computes the coefficient estimates and use them to re-compute the instrument, until convergence is achieved.

### 3.4. Social interaction and multiple equilibriums

The implications of the presence of social interaction in our choice model at the neighborhood level can be investigated on the basis of (5). We can interpret the right-hand side of this equation as a mapping of  $E(C_j)$ . To focus on essentials, we assume a population with individuals that are identical (apart from the idiosyncratic term in the logit model) and simplify (5) as:

$$E(C_j) = \frac{e^{\phi_j + \gamma E(C_j)}}{1 + e^{\phi_j + \gamma E(C_j)}} \quad (7)$$

It is not difficult to verify that:

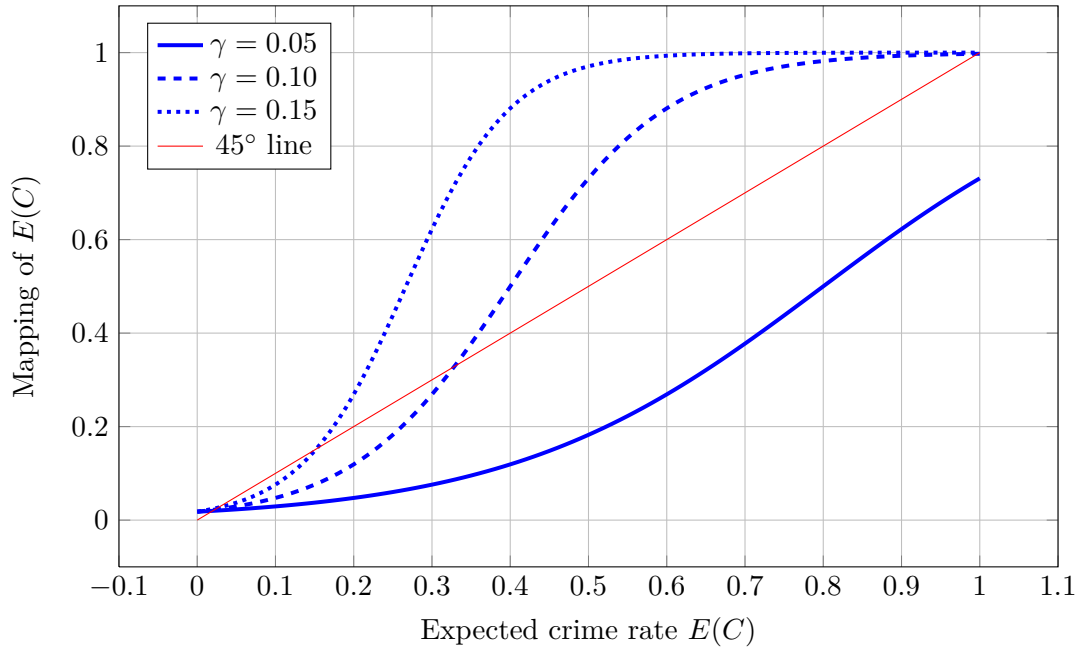
$$\frac{dE(C_j)}{d\phi_j} = \frac{1}{1 - \gamma E(C_j)(1 - E(C_j))} E(C_j)(1 - E(C_j)) \quad (8)$$

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<sup>2</sup> One can, for instance, use OLS estimation of (4).



The first term on the right-hand side is a multiplier that equals 1 if there is no social interaction ( $\gamma = 0$ ) and is larger than 1 whenever there is positive social interaction ( $\gamma > 0$ ). As noted above, this multiplier could be responsible for spatial variation in crime rates that is much larger than one would expect on the basis of a model without endogenous social interactions.



**Figure 1** – Possible equilibria for multiple forms of crime based on  $\phi_j = -4$  and various  $\gamma$ 's.

Brock and Durlauf (2001) provide an analysis of the equilibriums in this model. They show that for positive values of  $\gamma$  there may exist three equilibria. Figure 2 illustrates this situation for  $\phi_j = -4$  and various values of  $\gamma$ . For  $\gamma = 0.1$  and  $\gamma = 0.15$  there are indeed three equilibria. The high and stable equilibrium refers to a situation in which almost everybody is involved in criminal activities. In the other two equilibriums criminals are a minority, but the size of the minority differs significantly. The proportion of criminals equals either 1.5% or, depending on  $\gamma$ , 15%/33%, where the former equilibrium is stable and the latter is not. This example therefore suggests that the model can be consistent with the presence of a different proportion of criminals in neighborhoods that are similar

in all characteristics. Although the exact location of the equilibriums depends on the values of the parameters, our numerical experiments suggest that the crime rate at the stable equilibrium with the highest crime rate is unrealistically high.

## 4. Data

Criminal behavior is notoriously difficult to measure. Because it is morally objectionable and legally sanctioned, many people are unwilling to confess their involvement in crime, to law enforcement as well as to researchers. Although quite a few surveys ask adolescent subjects to report their involvement in criminal conduct (a few examples include Elliott et al., 1985; Farrington et al., 1996; Wikström et al., 2012) crime self-report surveys are rare among adult populations (but see Morselli and Tremblay, 2004).

To measure criminal behavior we therefore used anonymized national population data from the Dutch National Police. The police information system from which the data were extracted contains data on all individuals that have been arrested by the Dutch police as criminal suspects in a particular year. It is estimated that more than 90 percent are subsequently either convicted in court or imposed a fine or community service by the public prosecutor's office in lieu of prosecution (this often happens in the case of relatively minor crimes) (Blom et al., 2005). The data contain some personal characteristics (sex, age, country of birth, parents' countries of birth, postal code of residential address) and also contain details about all crimes of which the individual has been suspected (including the dates and the types of crime). In the analysis in this paper we use being a suspect of any crime(s) in the year 2006 as the dependent variable as well as separate indicators for being suspected of (i) violent and (ii) property crime (of course the two types do not exclude each other, so that a single person can be suspected of both crimes types within the same year). Because the police information system is used for investigative

purposes, it is updated continuously, and updates include changes of address as well as removal of individuals after an expiration period, the length of which depends on the seriousness of their criminal record. The database used in this analysis was an archival copy of the information system, and included crimes already removed from the real ‘living’ information system. Data from special investigative services are excluded, so that tax and other economic crimes, social security fraud, and environmental crimes are underrepresented.

There are also some (well-documented) disadvantages to using police records to measure criminality. First, a substantial percentage of crimes never comes to the attention of the police, either because there is not an individual victim to report it (e.g., drug dealing) or because the victim does not report the crime to the police (Goudriaan et al., 2004). Second, in most jurisdictions the police solve only approximately 20 percent of all crimes (Dodd et al., 2004). As a consequence, any estimate of criminality based on police data must be a severe underrepresentation. Third, specific surveillance or investigative strategies used by the police may result in some areas being more intensely supervised and investigated than others, resulting in an overrepresentation of these areas in the data. Fourth, police records have data on suspects, but some of these people may be unjustly suspected and will not be convicted subsequently in court. Notwithstanding these limitations police records are the best available large-scale measures of criminality available, and have been used extensively in previous studies in The Netherlands and abroad.

To obtain a full population dataset on criminal involvement in 2006 in The Netherlands, we used population data from Statistics Netherlands per January 1st, 2006, which cross-tabulates neighborhood of residence (4,028 neighborhoods) with age (20 categories, each 5 years width), sex (male versus female), and ethnicity (native versus non-native). As the police records contain these four variables as well, both sources can be combined to create a national dataset containing approximately 16 million individuals with the

following five variables:

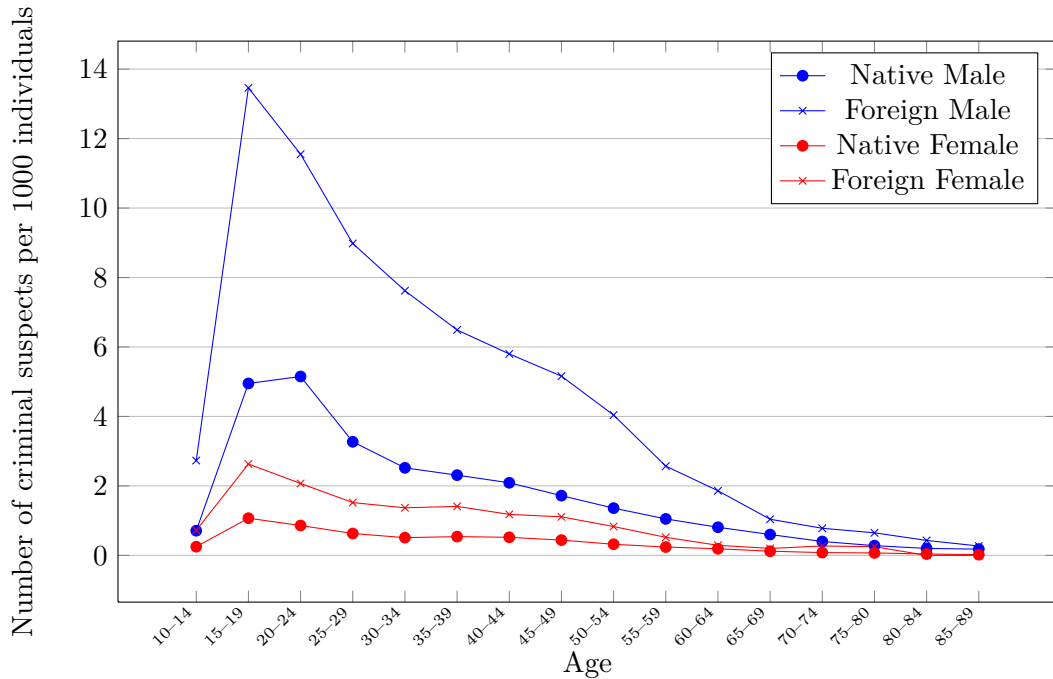
1. neighborhood of residence (4,028 neighborhoods);
2. sex (male or female);
3. non-native Dutch (individual or their parent(s) born in a non-western country, or not)
4. age (20 categories: 0-4 years, 5-9 years, 10-14 years, 15-19 years, etc. );
5. suspected of one or more violent/property crimes in 2006 (yes or no).

Because in The Netherlands only individuals of age 12 and older can be prosecuted, age categories 0-4 years and 5-9 years were removed from the analysis. Persons aged 10 or 11 are included because the population data are available only in 5-years age categories. Because no individuals above age 89 were prosecuted in 2006, ages 90 and above were also removed from the analysis. The remaining dataset contains 14,301,005 individuals aged 10-89 in 2006.

For this population, Figure 2 displays the number of individuals who were suspected of criminal involvement during the year 2006, per 1,000 residents of the same sex, age category and ethnic origin.<sup>3</sup> The figure confirms three stylized facts about criminality: the arrest rates of men are five times larger than those of women (Steffensmeier and Allan, 1996; Mears et al., 1998), the arrest rates of residents with foreign origin are more than 3 times larger than those of native Dutch residents (Blokland et al., 2010), and arrest rates of all groups peak during adolescence and early adulthood at ages 15-24 (Blokland et al., 2005). On average, 1.5 percent of the 10-89 population became a crime suspect in 2006. For boys in the age category 15-24 years, the percentage is more than

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<sup>3</sup>The data underlying Figure 2 are included in Table A.1 in the Appendix.



**Figure 2** – Number of criminal suspects in 2006 per 1,000 individuals, by age, sex, and ethnic origin.

four times larger than the average.

The police records include the six-digit postal codes of the residential addresses of the individuals. Throughout the Netherlands there are about 435,000 six-digit postal code areas. In non-rural areas they are roughly the size of a football field and contain approximately 20 residential properties and 40 residents. As they were created with pedestrian postal delivery services in mind, single codes are nearly always on the same street, apply to adjacent properties, and are not subdivided by physical barriers that impede pedestrian or car transportation. The focus of our investigation is the proportion of neighborhood residents involved in crime.<sup>4</sup> In line with definitions of ‘neighborhood’ as a locus of social interaction elsewhere in the literature, our analysis uses the four-digit

<sup>4</sup>When the peer group is located in the neighborhood, the chance of interaction with a criminal is affected not only by the relative number of criminals, but also by the size of the area. Thus, the social interaction effect can alternatively be defined as the percentage of residents per square mile exhibiting a given behavior.

Dutch postal code number as the spatial unit of analysis, i.e. a spatial aggregation of the six-digit postal code. Following Walker et al. (2011), we assume that “these postal code boundaries delineate spatial peers and that individuals within a postal code are more similar, exerting a stronger influence than individuals who live outside of one’s postal code” (p. 368). Many other studies in The Netherlands have used the four-digit postal code as a neighborhood delineation criterion (Wilsem et al., 2006; Nieuwbeerta et al., 2008; Bernasco and Kooistra, 2010).

Substantive arguments for neighborhood as a valid spatial reference group were already given in the literature overview. There are also several methodological arguments in favor of the neighborhood (instead of a larger or smaller areal unit). First and foremost, larger areas such as cities ensconce within-city heterogeneity (and therefore between-neighborhood differences) in criminality. Secondly, smaller areas than neighborhoods, such as streets, result in very skewed crime distributions that are more difficult to model properly. Thirdly, no or very little areal data are available at smaller spatial scales than neighborhoods. Because previous scholars (e.g., GSS) have used cities as units of analysis, we bolster our argument for smaller areal units by presenting the percentage of criminal suspects graphically for both municipalities and neighborhoods in The Netherlands in Figure 3. Figure 4 provides a view of neighborhoods in Amsterdam, the capital of The Netherlands. These figures show that the percentage of criminal suspects per municipality disguises large within-municipality differences. For example, whereas on average 2.2% of the population of Amsterdam was suspected of a crime in 2006 (and 1.8% and 1.2% for violent crime and property crime, respectively), the percentage of suspected criminals per neighborhood ranges from 0% to about 5% (0%–4% and 0%–3% for violent crime and property crime, respectively). Geographically, the Netherlands is a small country with a total land surface of 41,526 square kilometers. The total country consists of 4,028 four-digit postal code areas with an average surface of 10.31 square kilometer and an average population of 4,073 inhabitants. Similar to US census tracts, the sizes of these



**Figure 3** – Percentage of criminal suspects in 2006 per municipality and neighborhood.

‘neighborhoods’ depend on population density. In urban areas where population densities are high, the surfaces of neighborhoods tend to be relatively small, whereas they are larger in rural areas where population densities are low.

To account for possible spurious findings, we control for several ubiquitous variables in criminological research about neighborhood differences in crime. Classic and contemporary criminological studies have consistently found that high population turnover, ethnic heterogeneity, low socio-economic status and the presence of one-parent households correlate with higher crime rates (see Sampson and Groves, 1989; Bursik Jr. And Grasmick, 1993; Sampson et al., 1997; Glaeser and Sacerdote, 1999). These neighborhood characteristics are hypothesized to affect crime in two distinct ways: (*i*) by decreasing social cohesion and (expectations of) social control; (*ii*) by impeding proper socialization by parents and other neighborhood residents of youth. We therefore merge our dataset



**Figure 4** – Percentage of criminal suspects in 2006 Amsterdam neighborhoods.

with two additional neighborhood datasets. The first is the neighborhood data from the Dutch Central Bureau of Statistics from which we extract address density, percentage single person households, average household size, number of shops, percentage owner-occupied housing, school density and percentage single parent households. The second is the Geomarketing data from WDM Netherlands, which is in itself composed out of several (marketing) databases. This database gives us information about neighborhood mobility (in- and outmigration), average level of education, a measure for the average social class and the number of double income households within a neighborhood.

Finally, it is well conceivable that the impact of social interaction differs with residential density. Namely, denser neighborhoods might lead to more residential interaction because meeting probabilities are simply larger. To control for this effect we incorporate an interaction effect between social interaction and residential density.



## 5. Results

Table 1 presents the estimation results of equation (3), omitting the neighborhood specific constants  $\delta_j$ . The socio-demographic variables included are a sex indicator (0 for males, 1 for females), an ethnicity indicator (0 for native Dutch or born in a western country, 1 for people or one of their parents born in a non-western country), age (measured categorically as 10–14=−1, 15–19=0, 20–24=1, . . . , 85–89=14, i.e. centered on the peak of the age-crime curve) and age squared. Of the 4,007 neighborhoods there were 401 in which not a single resident offended in 2006, making it impossible to estimate a neighborhood specific constant term for the general model. In 409 neighborhoods not a single violent act of crime took place and property crime was absent in 802 neighborhoods.<sup>5</sup> The estimation

**Table 1** – Choice models (log-odds of being suspect of crime in 2006).

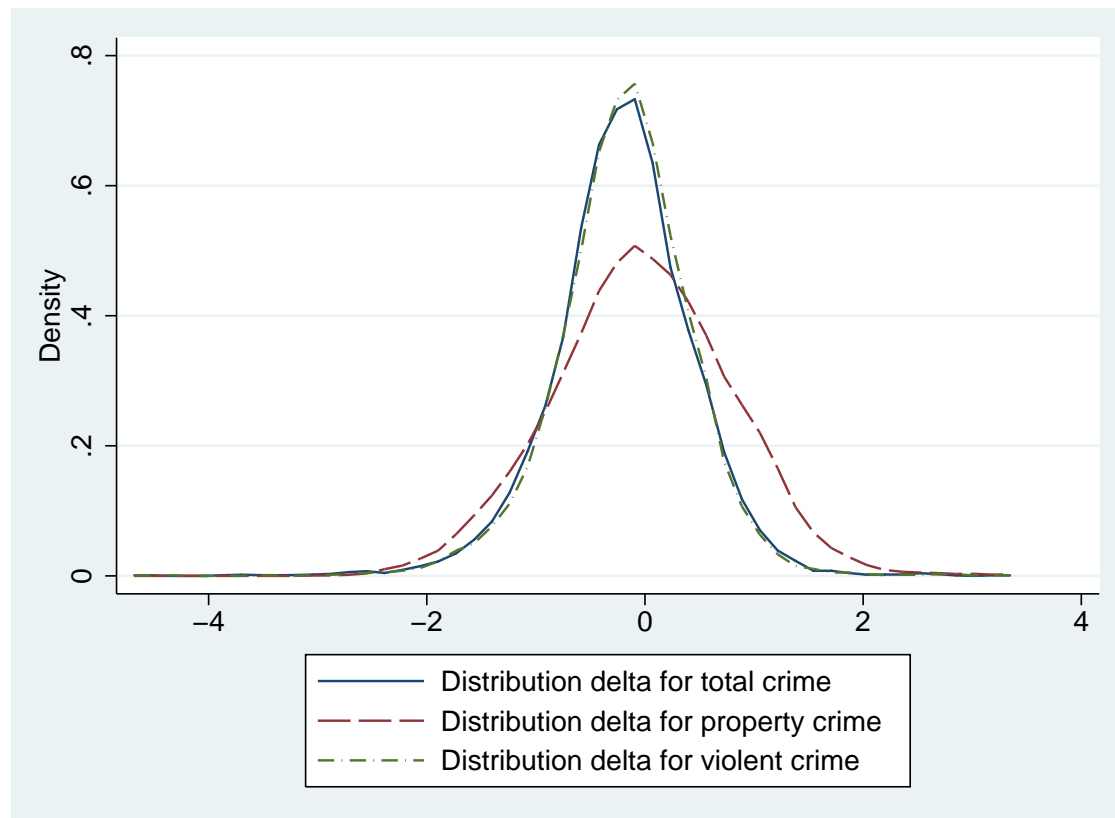
Parameter	All crime		Violent crime		Property crime	
	Estimation	S.E.	Estimation	S.E.	Estimation	S.E.
Female	−1.637	0.0059	−1.885	0.0069	−1.509	0.0085
Non-native	0.783	0.0059	0.743	0.0063	0.957	0.0081
Age	0.070	0.0019	0.109	0.0021	−0.110	0.0030
Age <sup>2</sup>	−0.026	0.0002	−0.030	0.0003	−0.034	0.0004
# Observations	14,191,721		14,189,082		13,966,926	
# Parameters	4 + 3,610 constants ( $\delta$ )		4 + 3,602 constants ( $\delta$ )		4 + 3,209 constants ( $\delta$ )	
Log-likelihood	−961,220.0		−855,499.9		−491,169.2	

results confirm the descriptive statistics visualized in Figure 2. Males and non-natives are much more likely to become involved in crime than females and native Dutch residents, and crime involvement first quickly increases with age and then gradually decreases. While the estimated parameters for violent crime are similar to the estimates for general crime, the property crime estimates indicate that the age-crime curve for property crime

<sup>5</sup>Usually, only the smallest neighborhoods with few or no criminals fall out of the estimation, which might invoke a selection bias. Note, however, that the number of observations decreases much slower than the number of neighborhoods.

peaks at younger ages.

A higher value of the neighborhood-specific constant  $\delta_j$  means that inhabitants of the neighborhood are more likely to be involved in crime. Because the first-stage model only imposes a structure on the effects of individual characteristics, it is silent about the mechanisms underlying between-neighborhood variation: these have to be sorted out in the second stage. The kernel density estimates of the shape of the  $\delta_j$  distributions are presented in Figure 5. All three density functions are single peaked and almost symmetric. The kernel density function of violent crime is similar to that of crime in general, whereas the kernel density function of property crime clearly has a higher mean and standard error.



**Figure 5** – Kernel density estimates of the distribution of  $\delta$ .

on our social interaction variable (*% involved in crime*) and interaction effect (*% involved*

*in crime*  $\times$  *# Addresses per hectare/1000*). Table 2 reports the second stage results of the regression on the  $\delta_j$ 's. As instruments of *% involved in crime* and *% involved in crime times # Addresses per hectare/1000* we have used the counterfactual crime rate,  $(IE(C_j))$ , as defined in eqn. (6), and the interaction effect of the counterfactual crime times the density,  $(IE(C_j) \times \text{Addresses per hectare}/1000)$ .

As Tables A.2 and A.3 in the Appendix clearly show, the instruments we use are relevant. The counterfactual crime rate is very significant and shows a positive correlation with *% involved in crime* as expected. The counterfactual crime rate times the density is very significant as well and shows a positive relation with *% involved in crime*  $\times$  *# Addresses per hectare/1000*. By construction, the counterfactual crime rate is uncorrelated with the error term  $\xi$ . The results of the second stage estimation are reported in Table 2.

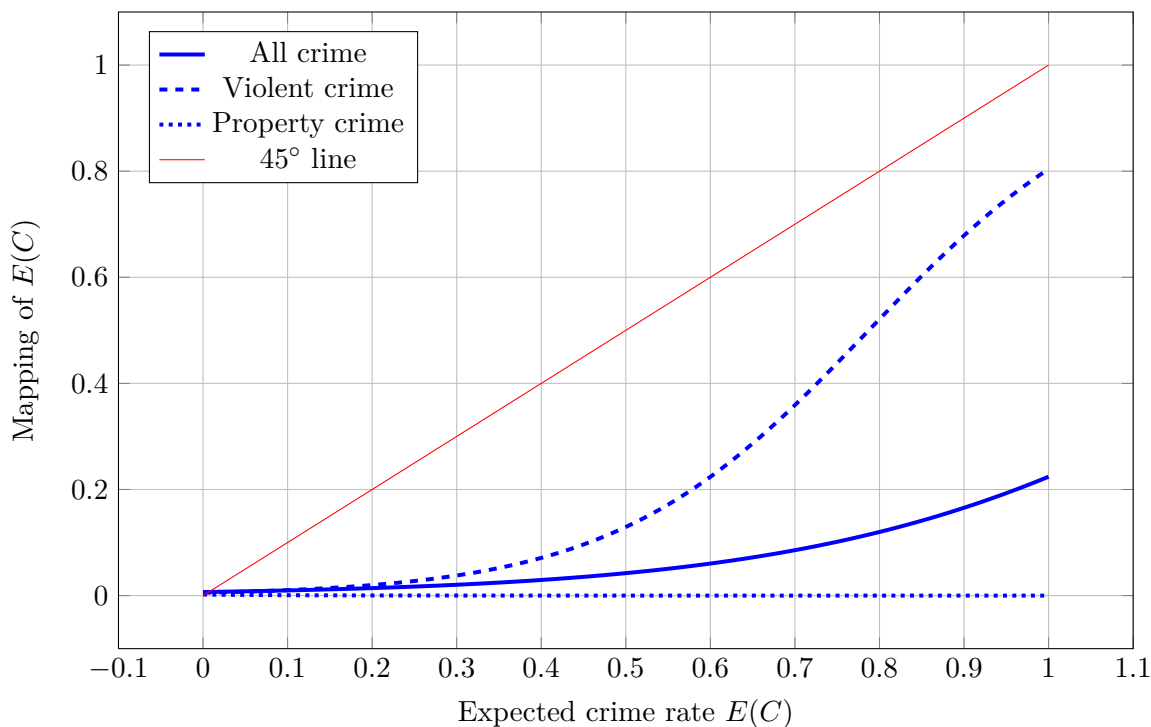
The main conclusion to be taken from the estimates in Table 2 is that the hypothesized social interaction effect (i.e., the effect of the neighborhood percentage of other residents involved in crime) is only significantly positive for violent crime, although its substantive impact is limited. For property crime and for overall crime the effects are completely insignificant. Thus, whereas it was hypothesized that a social interaction mechanism would apply to all types of crime but that its role in violent crime would be larger than its role in property crime, the findings demonstrate that the social interaction only plays a role in violent crime.

The estimates of the remainder of the variables in the second stage of the 2SLS estimation are in line with studies on neighborhood level correlates on crime and delinquency, which generally show that indicators of social and economic disadvantages (low education, low income, high neighborhood mobility and high proportions of single person and single parent households) are associated with more crime.<sup>6</sup> The large and highly significant

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<sup>6</sup>Our results are robust over years (for the years 2007 and 2008 we get similar results) and to the specification used. Only if we omit single parent households we get somewhat higher social interaction effects (up to  $\gamma = 0.13$ – $0.15$ ). Using different instruments, in particular the spatial lags of surrounding

coefficient on the share of single parent households is in line with earlier analyses (notably Glaeser and Sacerdote, 1999).



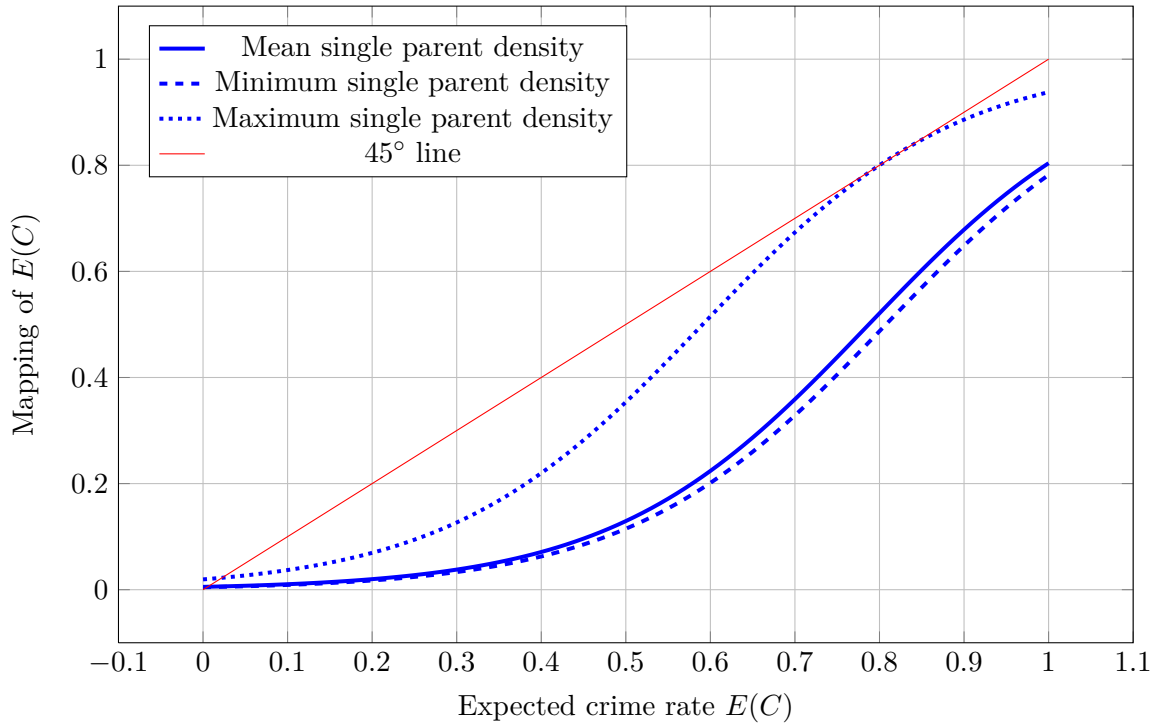
**Figure 6** – Possible equilibriums for multiple forms of crime based on parameter estimates.

Figure 6 illustrates the equilibriums as implied by the parameter estimates for the various forms of crime (regardless of the significance of the coefficients), based on the individual and neighborhood means. In this case, even the statistical significant coefficient for violent crime is not high enough to create multiple equilibriums. All estimated equilibriums are low and around the 1%.

Figure 7 illustrates that multiple equilibriums are possible for different values of neighborhood and individual variables. In this case, Figure 7 shows that the impact of the social interaction effects differs significantly over the whole range of empirical values of single parent density. For the empirical maximum of one-parent density (55%), multiple

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neighborhoods, does, however, significantly increase the social interaction effect (to more than  $\gamma = 0.4$ , which leads to completely criminal neighborhoods, a highly implausible outcome).



**Figure 7** – Possible equilibriums for various values of single parent density.

equilibriums are (just) possible.

## 6. Discussion

In a critique of the empirical literature on social interactions, Manski (2000) claims that their analysis would benefit from the performance of well-designed experiments in controlled environments and from careful elicitation of persons' subjective perceptions of the interactions in which they participate. Falk et al. (2010) adopt the first suggestion and demonstrate social interactions in an experiment on behavior in a public goods game. However, ethical considerations and IRB regulations prohibit experimental studies of criminal behavior of the type and severity that we study. Therefore, in the present paper we chose the second-best alternative, and estimated a structural discrete model using

state-of-the-art techniques to tease out social interactions with an exceptionally rich and comprehensive dataset.

On the basis of previous literature it was hypothesized that positive social interactions play a role in all crime, in particular in violent crime. The results of our analysis partially confirm this expectation. They indicate a positive and significant, but small, social interaction effect for violent crime only, but not for property crime or general crime. Apparently, social interaction is less influential in generating crime than was expected on the basis of prior research. We suggest that prior research may have overestimated endogenous social interaction effects by lack of individual data at a detailed spatial scale. In particular, we demonstrated that there exist huge individual differences in crime involvement by sex, age and ethnic background, which have hardly been accounted for in prior research on social endogenous interactions and crime.

Nevertheless, we did find a positive social interaction effect for violent crime. Apart from violent crime's reciprocal nature, another interpretation might be that social interactions apply to violent crime because violent crimes are overt predatory contact crimes that presume an interaction between the offenders and their victims. In neighborhoods where individuals live amongst others who are prone to violence, the risk of violent victimization is relatively high and might be lowered by gaining a reputation of 'toughness'. Thus, being a violent offender may deter violent predators and thereby prevent future violent victimization (Silverman, 2004; Fagan and Meares, 2008; Dur and Weele, 2012). The large majority of property crimes (larceny, burglary, etc.) are covert crimes that are perpetrated without any contact between the perpetrator and the victim, and without the victim being able to identify the perpetrator (and often also vice versa). For this reason, property offending does not yield any reputation to the perpetrator. Social interaction effects are therefore unlikely in the case of (covert) property crimes. Note that one should expect a social interaction effect on robbery, because although its purpose is

illegal property transfer, unlike other property crimes it involves direct contact between the perpetrator and the victim.

We conclude by noting some issues for future research. We found the share of single parent households to be an extremely important variable. We were, however, unable to test the hypothesis suggested by this finding, viz. that criminals often belong to such households. Another limitation of our study is that we have assumed that the social interaction effect is identical for all households whereas it is conceivable that some individuals (young adolescents, for instance) are more sensitive to such interactions than others. A third issue that has not been elaborated in this paper is that crime is notoriously difficult to measure. Some crimes are not reported to the police (more than 50 percent according to conservative estimates (Goudriaan et al., 2004), and that the police solve only 20 percent of the recorded crimes (Dodd et al., 2004). The annual percentage of the population involved in crime is thus an underestimate, and it implies there is some misclassification in the dependent variable of our analysis. Starting from the other side, there also exists a small risk of misclassification, namely when the police attributes a crime to an individual that actually did not perpetrate it. Given the fact that the police will only attribute it to a person if substantial evidence has been collected (enough for the suspect to be prosecuted), the likelihood of a ‘false positive’ is quite small. In future research, such misclassification issues might be dealt with. Lewbel (2000) has shown that binary discrete choice models with misclassification are non-parametrically identified and Hausman et al. (1989) provides techniques for estimating this model.

**Table 2** – 2SLS estimation on  $\delta$ —second stage

Parameter	All crime		Violent crime		Property crime	
	Estimation	S.E.	Estimation	S.E.	Estimation	S.E.
% Involved in crime	0.038	0.032	0.068*	0.033	-0.098	0.087
% Involved in crime $\times$						
# Addresses per ha./1000	-0.104	0.464	-0.186	0.547	-0.005	1.264
# Addresses per hectare/1000	-0.243	1.201	-0.218	1.240	0.470	1.808
% Single person households	-0.168	0.114	-0.261*	0.111	-0.084	0.178
% Single parent households	3.246***	0.397	0.589***	0.363	6.239***	0.641
# Persons per household	-0.217***	0.046	-0.203***	0.046	-0.583***	0.076
Education <sup>1</sup>	-0.252***	0.028	-0.239***	0.028	-0.440***	0.044
Social class <sup>2</sup>	0.059***	0.015	0.067***	0.015	0.056*	0.024
Double income households <sup>3</sup>	-0.062***	0.010	-0.067***	0.010	-0.050**	0.016
% Out migration <sup>4</sup>	0.003*	0.001	0.003*	0.001	0.004*	0.002
% In migration <sup>5</sup>	0.006***	0.001	0.005***	0.001	0.010***	0.002
School density	-0.001	0.001	-0.001	0.001	-0.002	0.002
% Homeowners/1000	0.705	0.597	0.929	0.597	1.097	0.970
# Shops/1000	0.122*	0.054	0.131*	0.055	0.055	0.084
Intercept	0.694***	0.144	0.668***	0.145	1.779***	0.238
# Observations	3,606		3,598		3,206	
R <sup>2</sup>	0.433		0.432		0.353	

Significance levels : \* : 5% \*\* : 1% \*\*\* : 0.1%

<sup>1</sup> Education: average education within neighborhood (defined as: 1 is low education; 2 is medium education; 3 is high education)

<sup>2</sup> Social class of neighborhood: running from high to low (4 categories: A, B1, B2 and C. For example A is high income; high education; own house)

<sup>3</sup> Double income households in neighborhood: average number of double income households, 9 categories running from low to high.

<sup>4</sup> Out migration: Total number of households that moved house from the neighborhood in the last five years relative to the total number of neighborhood households (in 10 classes from low to high).

<sup>5</sup> In migration: Total number of households that moved house to the neighborhood in the last five years relative to the total number of neighborhood households (in 10 classes from low to high).



## References

- Akers, R. L. (1985). *Deviant Behavior: A Social Learning Approach*. Belmont: California Wadsworth Publishing Company (cit. on p. 6).
- Ballester, C., Y. Zenou, and A. Calvo-Armengol (2010). “Delinquent Networks”. In: *Journal of the European Economic Association* 8.1, pp. 34–61 (cit. on p. 3).
- Bayer, P, R McMillan, and K Rueben (2004). “An Equilibrium Sorting Model of Sorting in an Urban Housing Market”. NBER, working paper no. 10865, Cambridge MA. (cit. on pp. 13, 14).
- Bayer, P and C Timmins (2007). “Estimating equilibrium models of sorting across locations”. In: *Economic Journal* 117.518, pp. 353–374 (cit. on p. 14).
- Becker, G. S. (1968). “Crime and Punishment: An Economic Approach”. In: *The Journal of Political Economy* 76.2, pp. 169–217 (cit. on p. 3).
- Beirne, P. (1987). “Adolphe Quetelet and the Origins of Positivist Criminology”. In: *The American Journal of Sociology* 92.5, pp. 1140–1169 (cit. on p. 3).
- Bernasco, W. and T. Kooistra (2010). “Effects of Residential History on Commercial Robbers’ Crime Location Choices”. In: *European Journal of Criminology* 7.4, pp. 251–265 (cit. on p. 20).
- Berry, S, J Levinsohn, and A Pakes (1995). “Automobile Prices in Market Equilibrium”. In: *Econometrica* 63.4, pp. 841–890 (cit. on pp. 5, 9–11).
- Blokland, A. A. J., D. S. Nagin, and P Nieuwebeerta (2005). “Life span offending trajectories of a dutch conviction cohort”. In: *Criminology* 43.4, pp. 919–954 (cit. on p. 18).
- Blokland, A. et al. (2010). “Criminaliteit en etniciteit: Criminele carrières van autochtone en allochtone jongeren uit het geboortecohort 1984”. In: *Tijdschrift voor Criminologie* 52, pp. 122–152 (cit. on p. 18).
- Blom, M et al. (2005). *Verdacht van criminaliteit: Allochtonen en autochtonen nader bekeken [Suspected of crime: Non-natives and natives examined more closely]*. Heerlen/Den Haag: CBS/WODC (cit. on p. 16).
- Brock, W. A. and S. N. Durlauf (2001). “Discrete choice with social interactions”. In: *Review of Economic Studies* 68.2, pp. 235–260 (cit. on pp. 5, 10, 11, 15).
- Bursik Jr., R. J. and H. G. Grasmick (1993). *Neighborhoods and Crime: The Dimensions of Effective Community Control*. New York: Lexington Books (cit. on p. 21).
- Calvo-Armengol, A. and Y. Zenou (2004). “Social networks and crime decisions: The role of social structure in facilitating delinquent behavior”. In: *International Economic Review* 45.3, p. 20 (cit. on p. 3).
- Case, A. C. and L. F. Katz (1991). *The Company You Keep: The Effects of Family and Neighborhood on Disadvantaged Youth*. Tech. rep. (cit. on p. 3).
- Dodd, T et al. (2004). “Crime in England and Wales 2003/2004.” Home Office Statistical Bulletin No.10/04. London: Home Office (cit. on pp. 17, 29).
- Dur, R. and J. van der Weele (2012). “Status-Seeking in Criminal Subcultures and the Double Dividend of Zero-Tolerance”. In: *Journal of Public Economic Theory* forthcoming (cit. on p. 28).

- Elliott, D. S., D. Huizinga, and S. S. Ageton (1985). *Explaining Delinquency and Drug Use*. Beverly Hills, CA: Sage (cit. on p. 16).
- Fagan, J. and T. L. Meares (2008). “Punishment, Deterrence and Social Control: The Paradox of Punishment in Minority Communities”. In: *Ohio State Journal of Criminal Law* 6, pp. 173–229 (cit. on p. 28).
- Falk, A., U. Fischbacher, and S. Gächter (2010). “Living in Two Neighborhoods: Social Interaction Effects in the Laboratory”. In: *Economic Inquiry* (cit. on p. 27).
- Farrington, D. P. et al. (1996). “Self-reported delinquency and a combined delinquency seriousness scale based on boys, mothers, and teachers: Concurrent and predictive validity for African-Americans and Caucasians”. In: *Criminology* 34.4, pp. 493–517 (cit. on p. 16).
- Festinger, L, S Schachter, and K Back (1950). *Social Pressures in Informal Groups: A Study of Human Factors in Housing*. New York: Harper (cit. on p. 7).
- Freeman, S, J Grogger, and J Sonstelie (1996). “The Spatial Concentration of Crime”. In: *Journal of Urban Economics* 40.2, pp. 216–231 (cit. on p. 3).
- Friendly, M. (2007). “A.-M. Guerry’s Moral Statistics of France: Challenges for Multi-variable Spatial Analysis”. In: *Statistical Science* 22, pp. 368–399 (cit. on p. 3).
- Glaeser, E. L. and B. Sacerdote (1999). “Why is There More Crime in Cities”. In: *Journal of Political Economy* 107.S6, pp. 225–258 (cit. on pp. 21, 26).
- Glaeser, E. L., B. Sacerdote, and J. A. Scheinkman (1996). “Crime and Social Interactions”. In: *The Quarterly Journal of Economics* 111.2, pp. 507–548 (cit. on p. 3).
- Gottfredson, M. R. and T Hirschi (1990). *A general theory of crime*. Palo Alto: Stanford University Press (cit. on p. 6).
- Goudriaan, H, J. P. Lynch, and P Nieuwbeerta (2004). “Reporting to the police in Western nations: A theoretical analysis of the effects of social context”. In: *Justice Quarterly* 21.4, pp. 933–969 (cit. on pp. 17, 29).
- Hausman, J. A., J Abrevaya, and F. M. Scott-Morton (1989). “Misclassification of the dependent variable in a discrete-response setting”. In: *Journal of Econometrics* 87, pp. 239–269 (cit. on p. 29).
- Lewbel, A (2000). “Identification of the binary choice model with misclassification”. In: *Econometric Theory* 16, pp. 203–209 (cit. on p. 29).
- Manski, C. F. (1988). “Identification of Binary Response Models”. In: *Journal of the American Statistical Association* 83.403, pp. 729–738 (cit. on p. 12).
- (1993). “Identification of Endogenous Social Effects: The Reflection Problem”. In: *Review of Economic Studies* 60, pp. 531–542 (cit. on pp. 5, 11).
- (2000). “Economic analysis of social interactions”. In: *Journal of Economic Perspectives* 14.3, pp. 115–136 (cit. on pp. 3, 27).
- Mears, D. P., M Ploeger, and M Warr (1998). “Explaining the gender gap in delinquency: Peer influence and moral evaluations of behavior”. In: *Journal of Research in Crime and Delinquency* 35.3, pp. 251–266 (cit. on p. 18).
- Morselli, C and P Tremblay (2004). “Criminal achievement, offender networks and the benefits of low self-control”. In: *Criminology* 42.3, pp. 773–804 (cit. on p. 16).

- Nieuwbeerta, P et al. (2008). “Neighborhood characteristics and individual homicide risks - Effects of social cohesion, confidence in the police, and socioeconomic disadvantage”. In: *Homicide Studies* 12.1, pp. 90–116 (cit. on p. 20).
- Patacchini, E. and Y. Zenou (2012). “Juvenile Delinquency and Conformism”. In: *Journal of Law, Economics, and Organization* 28.1, pp. 1–31 (cit. on p. 7).
- Sampson, R. J., S. W. Raudenbush, and F Earls (1997). “Neighborhoods and violent crime: A multilevel study of collective efficacy”. In: *Science* 277.5328, pp. 918–924 (cit. on p. 21).
- Sampson, R. J., T. Gannon-Rowley, and J. D. Morenoff (2002). “Assessing “Neighbourhood Effects”: Social Processes and New Directions in Research”. In: *Annual Review of Sociology* 28, pp. 443–78 (cit. on p. 8).
- Sampson, R. J. and W. B. Groves (1989). “Community Structure and Crime: Testing Social Disorganization Theory”. In: *American Journal of Sociology* 94, pp. 773–802 (cit. on p. 21).
- Shaw, C. R. and H. D. McKay (1969). *Juvenile Delinquency and Urban Areas*. Chicago: University of Chicago Press (cit. on p. 8).
- Silverman, D. (2004). “Street Crime and Street Culture”. In: *International Economic Review* 45.3, pp. 761–786 (cit. on p. 28).
- Steffensmeier, D and E Allan (1996). “Gender and crime: Toward a gendered theory of female offending”. In: *Annual review of sociology* 22, pp. 459–487 (cit. on p. 18).
- Sutherland, E. H. (1947). *Principles of criminology*. Chicago: University of Chicago Press (cit. on p. 6).
- Sykes, G. M. and D Matza (1957). “Techniques of Neutralization - A Theory of Delinquency”. In: *American sociological review* 22.6, pp. 664–670 (cit. on p. 6).
- Walker, J. L. et al. (2011). “Correcting for endogeneity in behavioral choice models with social influence variables”. In: *Transportation Research Part A-Policy and Practice* 45.4, pp. 362–374 (cit. on pp. 9, 10, 12, 20).
- Weerman, F. M. (2011). “Delinquent Peers in Context: A Longitudinal Network Analysis of Selection and Influence Effects”. In: *Criminology* 49.1, pp. 253–286 (cit. on p. 7).
- Wikström, P.-O. H. et al. (2012). *Breaking Rules: The Social and Situational Dynamics of Young People’s Urban Crime*. Oxford: Oxford University Press (cit. on p. 16).
- Wilsem, J. van, K. Wittebrood, and N. D. de Graaf (2006). “Socioeconomic Dynamics of Neighborhoods and the Risk of Crime Victimization: A Multilevel Study of Improving, Declining, and Stable Areas in the Netherlands”. In: *Social Problems* 53, pp. 226–247 (cit. on p. 20).
- Zenou, Y. (2003). “The Spatial Aspects of Crime”. In: *Journal of the European Economic Association* 1.2-3, pp. 459–467 (cit. on p. 3).

## A. Appendix: Tables

**Table A.1** – Number of criminal suspects in 2006 per 1,000 individuals, by age, sex and ethnic origin.

Age	Male			Female			Total male and female		
	Native	Foreign	Total male	Native	Foreign	Total female	Total native	Total foreign	Grand total
10–14	0.71	2.73	1.02	0.25	0.72	0.32	0.48	1.75	0.68
15–19	4.95	13.46	6.27	1.07	2.63	1.31	3.05	8.20	3.84
20–24	5.15	11.55	6.21	0.86	2.07	1.06	3.03	6.80	3.67
25–29	3.27	8.98	4.17	0.63	1.52	0.78	1.96	5.12	2.47
30–34	2.52	7.62	3.23	0.51	1.37	0.64	1.52	4.40	1.94
35–39	2.31	6.49	2.82	0.54	1.41	0.64	1.43	4.00	1.74
40–44	2.09	5.80	2.50	0.52	1.18	0.59	1.31	3.61	1.56
45–49	1.72	5.16	2.02	0.44	1.11	0.50	1.08	3.18	1.27
50–54	1.36	4.04	1.53	0.32	0.83	0.36	0.84	2.41	0.95
55–59	1.05	2.57	1.13	0.24	0.52	0.26	0.65	1.54	0.70
60–64	0.81	1.86	0.86	0.19	0.29	0.19	0.50	1.13	0.53
65–69	0.60	1.04	0.62	0.12	0.20	0.12	0.35	0.67	0.36
70–74	0.40	0.78	0.41	0.08	0.27	0.09	0.23	0.53	0.24
75–79	0.28	0.65	0.28	0.07	0.25	0.07	0.15	0.42	0.16
80–84	0.20	0.43	0.20	0.04	0.00	0.04	0.09	0.15	0.10
85–89	0.18	0.27	0.18	0.02	0.00	0.02	0.07	0.08	0.07
Total	1.99	7.00	2.49	0.41	1.36	0.50	1.19	4.21	1.49

Source: Statistics Netherlands and Netherlands National Police Services (KLPD)

**Table A.2** – 2SLS estimation on  $\delta$ —first stage regression on % *Involved in crime*

Parameter	All crime		Violent crime		Property crime	
	Estimation	S.E.	Estimation	S.E.	Estimation	S.E.
$IE(C_j)$	0.819***	0.046	0.925***	0.051	0.737***	0.065
$IE(C_j) \times \#$ Addresses per hectare/1000	0.002**	0.001	0.001	0.001	0.004***	0.001
# Addresses per ha./1000	-2.374	1.802	-0.423	1.713	3.992**	1.383
% Single person households	-0.215	0.202	0.038	0.174	-0.235	0.185
% Single parent households	-0.689	0.719	-1.103	0.611	-0.639	0.659
# Persons per household	-0.203*	0.081	-0.106	0.073	-0.200**	0.074
Education <sup>1</sup>	-0.162***	0.045	-0.108*	0.041	-0.064	0.040
Social class <sup>2</sup>	0.002	0.026	-0.001	0.023	0.014	0.023
Double income households <sup>3</sup>	0.005	0.017	0.002	0.016	0.005	0.015
% Out migration <sup>4</sup>	0.001	0.002	0.001	0.002	0.001	0.002
% In migration <sup>5</sup>	0.001	0.002	0.000	0.002	0.001	0.002
School density	-0.002	0.002	-0.002*	0.002	-0.004*	0.002
% Homeowners/1000	0.741	1.022	0.891	0.931	-1.451	0.910
# Shops/1000	-0.127	0.094	-0.145	0.085	-0.058	0.079
Intercept	0.114***	0.242	0.668***	0.145	0.944***	0.220
# Observations	3,606		3,598		3,206	
R <sup>2</sup>	0.564		0.519		0.445	
Test of excluded instruments	310.14***		303.20***		155.37***	

Significance levels : \* : 5% \*\* : 1% \*\*\* : 0.1%

<sup>1</sup> Education: average education within neighborhood (defined as: 1 is low education; 2 is medium education; 3 is high education)

<sup>2</sup> Social class of neighborhood: running from high to low (4 categories: A, B1, B2 and C. For example A is high income; high education; own house)

<sup>3</sup> Double income households in neighborhood: average number of double income households, 9 categories running from low to high.

<sup>4</sup> Out migration: Total number of households that moved house from the neighborhood in the last five years relative to the total number of neighborhood households (in 10 classes from low to high).

<sup>5</sup> In migration: Total number of households that moved house to the neighborhood in the last five years relative to the total number of neighborhood households (in 10 classes from low to high).

**Table A.3** – 2SLS estimation on  $\delta$ —first stage regression on *% Involved in crime*  $\times$  *# Addresses per hectare/1000*

Parameter	All crime		Violent crime		Property crime	
	Estimation	S.E.	Estimation	S.E.	Estimation	S.E.
$IE(C_j)$	-3.480**	1.260	-4.144**	1.397	-3.904*	1.706
$IE(C_j) \times \#$ Addresses per hectare/1000	0.967***	0.019	0.970***	0.022	0.957***	0.025
# Addresses per ha./1000	287.93***	49.100	279.66***	47.160	180.14***	16.423
% Single person households	8.773	5.511	8.797	4.785	18.138***	4.861
% Single parent households	41.576*	19.592	36.816*	16.818	20.231	17.367
# Persons per household	-3.005	2.214	-2.125	2.009	2.088	1.946
Education <sup>1</sup>	-6.269***	1.230	-5.525***	1.140	-3.499**	1.065
Social class <sup>2</sup>	1.937**	0.699	1.791**	0.643	0.787	0.600
Double income households <sup>3</sup>	2.237***	0.472	1.856***	0.434	1.356**	0.406
% Out migration <sup>4</sup>	-0.065	0.054	0.068	0.050	-0.102*	0.046
% In migration <sup>5</sup>	0.032	0.049	0.033	0.044	0.033	0.042
School density	-0.073	0.057	-0.055	0.053	-0.036	0.054
% Homeowners/1000	129.91***	27.848	122.59***	25.638	33.215	23.990
# Shops/1000	4.125**	2.549	4.295	2.353	6.485**	2.090
Intercept	-6.147	6.608	-6.634	6.108	-13.041*	5.802
# Observations	3,606		3,598		3,206	
R <sup>2</sup>	0.919		0.907		0.857	
Test of excluded instruments	1927.88***		1499.38***		1065.50***	

Significance levels : \* : 5% \*\* : 1% \*\*\* : 0.1%

<sup>1</sup> Education: average education within neighborhood (defined as: 1 is low education; 2 is medium education; 3 is high education)

<sup>2</sup> Social class of neighborhood: running from high to low (4 categories: A, B1, B2 and C. For example A is high income; high education; own house)

<sup>3</sup> Double income households in neighborhood: average number of double income households, 9 categories running from low to high.

<sup>4</sup> Out migration: Total number of households that moved house from the neighborhood in the last five years relative to the total number of neighborhood households (in 10 classes from low to high).

<sup>5</sup> In migration: Total number of households that moved house to the neighborhood in the last five years relative to the total number of neighborhood households (in 10 classes from low to high).

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