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Individual and neighbourhood determinants of adolescent aggressive behaviour : a multilevel analysis

INDIVIDUAL AND NEIGHBOURHOOD DETERMINANTS OF ADOLESCENT AGGRESSIVE BEHAVIOUR: A MULTILEVEL ANALYSIS

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Abstract

This research examines the extent to which, individual and neighbourhood characteristics contribute to the risk of two different types of adolescent aggressive behaviour: aggression and delinquency. In addition, it explores potential mechanisms explaining the influence of neighbourhood conditions on adolescent aggressive behaviour. Data regarding adolescent behaviour is taken from self-reported surveys, applied to 1,686 Colombian adolescents, residing in 103 neighbourhoods. Data regarding neighbourhoods is taken from official government datasets, as well as two community surveys that are independent of the individual aggression survey. A range of statistical approaches is used to develop reliable valid measures of both adolescent aggressive behaviour and neighbourhood characteristics: multilevel Rasch models, multilevel factor analysis, ecometrics, spatial multiple membership models, Geographic Information Systems and hierarchical Bayes procedures. For the analysis, the research develops an explicit conceptual framework and uses multilevel modelling and multilevel structural equation modelling to obtain unbiased estimates of overall effects, cross-level interactions, direct and indirect effects. Results indicate that individual and neighbourhood-level factors are not only directly and indirectly associated with adolescent aggressive behaviour, but also interact with one another to shape adolescent behaviour. By identifying the processes through which neighbourhoods constrain, enhance or modify adolescent behaviours, these results may be used to inform community based programs, aiming to reduce adolescent aggressive behaviour.

Dedication

To God and all his gifts that made the years of my PhD in Bristol so enjoyable and successful.

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Author's declaration

I declare that the work in this thesis was carried out in accordance with the requirements of the University's Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the thesis are those of the author.

SIGNED: ...Beatriz Caicedo... DATE: Feb 16/12

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Chapter 1. Introduction: the scope and approach of the study

The primary aim of this research is to examine the relations between individual and neighbourhood factors and adolescent aggressive behaviour. In particular, attention focuses on the effects of neighbourhood structural and social conditions on adolescent aggressive behaviour. This study has three distinctive features: i) a developed theory of the mechanisms that link neighbourhood characteristics to aggressive behaviour; ii) the use of multilevel methods to measure both adolescent aggressive behaviour and neighbourhood characteristics; and iii) the use of multilevel mediational and moderation models to evaluate the evidence that neighbourhood conditions direct and indirectly affect adolescent aggressive behaviour as well as interact with individual factors to produce it. The study is undertaken in the Colombian city of Medellin which has an unenviable international reputation for aggression and crime.

Technically, the term aggressive behaviour is defined as a component of antisocial behaviour that consists of behaviours by individuals that intentionally threaten, attempt or inflict physical or psychological harm on others including children, adults, and animals (Reiss et al., 1994, Ecob and Macintyre, 2000). The current study uses the term *aggressive behaviour* to mean antisocial behaviours related to threatening, hitting, and hurting someone with/without a gun, as well as robbery and murder.

The research presented here investigates cross-sectional data from Medellin –northwest Colombia—, where adolescent aggressive behaviour continues to be a significant public health concern, despite many prevention efforts (Duque et al., 2011b, Duque et al., 2007). Estimates from a cross-sectional population survey in the urban area of Medellin in 2007 showed that 33.2% of the adolescents aged 12 to 17 years old had engaged in a fight during the previous year, while in their lifetime 4.7% had participated in an unarmed robbery, 1.6% had engaged in a sexually aggressive act, and 0.8% had committed armed physical aggression (Duque et al., 2011a). Similar prevalences are reported in 2005 by the Youth Risk Behaviour Surveillance System in the United States, where 35.9% of high school students reported having engaged in a physical fight during the previous 30 days, 9.9% had driven a car when they had been drinking alcohol and 18.5% had carried a weapon in the previous 30 days (Eaton et al., 2006).

Adolescent aggressive behaviour is an area of great interest to public health and criminology researchers. This is mainly for two reasons. First, early manifestation of aggressive behaviour is found to be a strong predictor of adulthood criminality and other social disorders such as substance abuse, academic failure, depression, spouse abuse and neglectful and abusive parenting (Tremblay et al., 2005). Second, several studies, including two Colombian studies (Duque et al., 2003, Duque and Klevens, 2000), have found that although the population of aggressors that commit the most serious or severe crimes (e.g. theft, armed assault, or sexual assault), is small, they account for a disproportionate number of offences (Farrington, 1995, Farrington and West, 1993, Farrington et al., 2001). Consequently, a large body of research has focused on establishing the multifaceted causes of aggressive behaviour that support the design and formulation of more effective prevention programmes (Loeber, 1997, Farrington, 1995, Tremblay, 2000).

According to the current empirical evidence (extensively reviewed in Chapter Two), no single factor is sufficient nor necessary for explaining why some individuals behave more aggressively than others, nor why violence is more prevalent in some communities than in others (Farrington, 1993, Farrington and Loeber, 2000). It has been demonstrated that a complex chain of environmental and individual variables are more likely to explain aggressive behaviour than any single variable. To understand this multifaceted nature of adolescent aggressive behaviour, researchers (Duque et al., 2011b, Duque, 2005, Krug et al., 2002) adapted the Ecological Systems Theory of Bronfenbrenner

(1979), which explains aggressive behaviour as the result of the interplay of risk factors at four different levels: individual, family, peer and community. Supporting the importance of each of these levels, current empirical research has frequently reported that young males from low socioeconomic background, who have been victimized or witnessed violence at home or in the neighbourhood, are at an increased risk of developing aggressive behaviour (Tremblay, 2000, Loeber and Dishion, 1983). Others have found strong evidence about the protective role of parenting characteristics such as monitoring or supervision, consistent discipline strategies, and warm and supportive relationships (Haapasalo and Tremblay, 1994, Farrington, 1995). Similarly, it has been argued that adolescents who are associated with deviant peers are more likely to engage in aggression, substance use and delinquency. Conversely, stability in prosocial peer relationships has been found to be protective (Farrington, 1993, Duncan et al., 2000, Loeber, 1997).

With regard to the fourth level of the ecological model, there are fewer empirical studies of community and neighbourhood influences. However, what which is available has consistently demonstrated that neighbourhood conditions such as ethnic composition, residential instability and neighbourhood disadvantage are key determinants of aggressive behaviour (Leventhal and Brooks-Gunn, 2003, Oberwittler, 2004, Jencks and Mayer, 1990, Leventhal and Brooks-Gunn, 2000). Other factors, such as the layout of the places, the availability of services and institutions and the degree of violence within the neighbourhood have also been highlighted as important factors especially in urban communities.

Despite the theoretical and empirical support for this ecological viewpoint, the bulk of current research has largely ignored it. In contrast, most research has focused on what Sampson (2006) calls a 'risk-factor approach' where the main object of interest is the correlation between neighbourhood conditions and individual behaviour, rather than on an 'explanatory-approach' where the research concentrates on the underlying mechanisms that lie behind such relationships. In contrast, this ecological perspective is used in the present research to investigate not only the associated factors, but also to understand more fully the processes through which the effect of neighbourhood conditions may be transmitted to adolescents.

A central principle of the Bronfenbrenner (1979) ecological theory is that the individual development of adolescents should be seen as the result not only of their individual conditions and of the qualities of the social environments in which they live or participate, but also of the extent and nature of the interaction between these contexts. This is moderation whereby adolescent behaviour is dependent not only on individual or neighbourhood characteristics, but on '*who is in what setting*' (Zimmerman, 2010). For example, Molnar *et al.* (2008) found that in neighbourhoods with high levels of positive social processes, adolescents with family support, prosocial peers and with non-parental mentors are significantly at lower risk of aggression than adolescents in neighbourhoods with poor social processes with the same individual conditions. Moreover, Rankin and Quane (2002) found that in neighbourhoods with low collective efficacy, adolescents who are monitored by their parents have lower risk of problems behaviours; however, in high collective efficacy neighbourhoods such monitoring confers less protection. Together, these results give support to what is known in neighbourhood literature as cross-level interactions, a promising venue of research that may lead to important advances in the knowledge of the complex role of places in shaping adolescent aggressive behaviour. Consequently, a complete analysis of aggressive behaviour must incorporate not only the analysis of 'kinds of individuals' and the 'kinds of neighbourhoods', but also the analysis of 'certain kinds of individuals in certain kinds of neighbourhoods' (Lynam et al., 2000, Zimmerman, 2010).

The ecological model also underpins cause-effect approaches that invoke the idea of mediation or the mechanisms by which some variables exert influences on others directly or through intervening or mediating variables (MacKinnon et al., 2000). Thus, evidence suggests that disadvantaged neighbourhoods have higher rates of juvenile crime and youth violence than less disadvantaged neighbourhoods, and that these associations are largely explained by social processes within the neighbourhood (Raudenbush and Sampson, 1999a, Kohen et al., 2008). Similarly, unfavourable neighbourhood conditions are seen to set adolescents off on paths leading to aggressive behaviour. Evidence indicates that, for example, parents living in violent and disadvantaged neighbourhoods tend to use stricter discipline strategies, which in turn increase associations with delinquent peers, a factor that is strongly associated with adolescent aggressive behaviour. In light of this empirical evidence, incorporating and testing the mediating roles of neighbourhood social processes, parenting practices and deviant peers within a single overall framework of analysis stands as a necessary challenge.

The purpose of this research is to test a hypothetical model of aggressive behaviour taking into account the multiple domains of the Bronfenbrenner (1979) ecological model. By doing so, it is possible to identify the more important factors related to adolescent aggressive behaviour, as well as to explore how individual and neighbourhood characteristics interact to produce adolescent aggressive behaviour. The overall aim is to evaluate the empirical support for hypothesised mechanisms through which neighbourhood conditions influence adolescent behaviour.

It is hoped that the results derived from this research will contribute to the formulation and implementation of community strategies aimed at reducing and preventing aggressive behaviour. As is well known, most, if not all, public health interventions are context-specific. Therefore, documenting neighbourhood factors that may contribute to modifying the effect of the individual variables on adolescent aggressive behaviour, as well as about the more proximal factors that transfer such distal effect, is essential for effective prevention strategies. To date no study in Colombia has simultaneously considered the effect of neighbourhood and individual factors on adolescent aggressive behaviour, neither exploring potential causal mechanisms nor potential cross-level interactions relevant to adolescent aggressive behaviour. Indeed such an approach has had limited application in any developing world setting. Thus, an additional purpose of this thesis is to contribute to the neighbourhood literature with data from Colombia, which can be further used to carry out cross-national comparisons of aggressive behaviour, as well as the important risk factors and mechanisms in this potentially different social and cultural context.

The overall approach is represented in Figure 1. Before proceeding to describe the proposed model, it is important to clarify the conceptual distinction between mediator, confounder and moderator variables. In general, mediator variables refer to variables that explain in full or part of the relationship between an independent variable (e.g. neighbourhood condition) and an outcome (e.g. aggressive behaviour). It is said that these variables are on the causal pathway between the cause and the effect (MacKinnon et al., 2000). The concept of confounding variable refers to third variables that also obscure or accentuate the relationship. However, unlike the mediator variables, confounders are not intermediate variables in the causal pathway between the independent variable and the outcome. Finally, moderator variables are variables that change or modify the effect of an independent variable on the outcome. When individuals and neighbourhood are concerned, this moderation may involve cross-level interactions (MacKinnon et al., 2000, Greenland and Morgenstern, 1989).

In the proposed model, it is hypothesized that neighbourhood structural and social characteristics may exert an effect on adolescent aggressive behaviour, over and above the effect of the individual confounders (shown by the solid line). It is also hypothesized that neighbourhood structural conditions have also an indirect effect via their impact on mediator variables such as neighbourhood social processes, parenting practices and peer influences (dashed lines in Figure 1). The aim of the study is therefore to evaluate empirically the size and nature of these overall effects and the indirect pathways. Finally, the study evaluates whether there are differential effects of individual predictors on adolescent aggressive behaviour in relation to specific neighbourhood conditions (the curved line in the figure). Given the cross-sectional nature of the data, the aim with this hypothesized model cannot be to establish causality; rather it is to explore potentially significant relationships between neighbourhood conditions and adolescent aggressive behaviour.

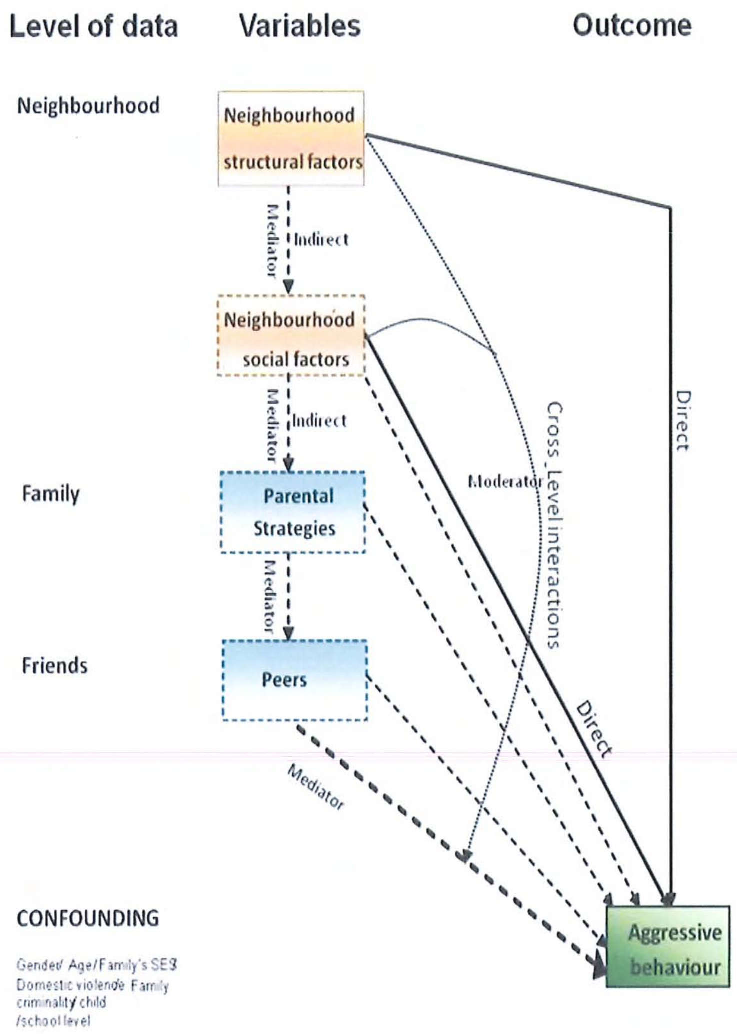


Figure 1. Schematic representation of possible direct, indirect, and cross-level interaction effects on pathways linking neighbourhood characteristic to aggressive behaviour

Thesis organization

This thesis is organized into seven chapters. Chapter One (this one) has set the scene, outlined the approach and defined the broad research questions that are to be investigated. Chapter Two presents a summary of the literature, including competing theories, previous work examining the relationship among individual factors, neighbourhood and adolescent aggressive behaviour, and the methodological difficulties faced by neighbourhood researchers. Chapter Three is concerned with the measurement of individual aggressive behaviour. This is achieved by defining a key set of properties that constitute valid and consistent measurement which are evaluated and achieved through an Item Response Theory (Rasch) multilevel model which takes as its input a set of individual self-reported items related to different acts of aggressive behaviour. The output from this model is two scales of measurement, labelled 'aggression' and 'delinquency', and these become the dependent variables in the subsequent models. Chapter Four extends the measurement model of Chapter Three to measure not only the individual underlying propensity of aggression and delinquency, but also the neighbourhood propensity of these two dimensions and to evaluate their geographical variation across the city. Chapter Five uses the theoretical literature to define characteristics of neighbourhoods and applies a range of advanced statistical techniques to model and measure reliably characteristics of neighbourhoods. This is done on the basis of administrative datasets and two community surveys which are independent of the individual aggression survey. Chapter Six addresses the relationship between individual and neighbourhood characteristics and aggressive behaviour. From a causal model perspective, much of the empirical literature does not make a clear distinction between confounders, mediators and true exposures in estimating neighbourhood effects. In contrast, this chapter develops an explicit conceptual framework and uses multilevel mediational modelling to assess both direct and indirect effects. A final chapter, Seven, draws conclusions, discusses study limitations, considers applications for future research and discusses the implications of the research for prevention.

Chapter 2. Previous research investigating neighbourhood effects on adolescent aggressive behaviour

The aim of this chapter is to critically review previous research on neighbourhood effects on adolescent aggressive behaviour. The chapter begins by discussing the different methods used for measuring aggressive behaviour. This is followed by a consideration of the theoretical bases of the mechanisms through which neighbourhood characteristics may shape adolescent aggressive behaviour. This is in turn followed by a concise summary of all the identified empirical studies that have examined the relationships among neighbourhood context, and aggressive behaviour. The final section of the chapter discusses the methodological problems that affect the study of neighbourhood effects.

Defining and measuring aggressive behaviour

Aggressive behaviour is not a unitary term but consist of different manifestations of antisocial behaviour including verbal aggression, bullying, physical fighting and different forms of violence, such as robbery, rape and homicide (Loeber, 1997). Typically, social science researchers use two different approaches for measurement (Farrington et al., 1996). The first relies on official records maintained by law enforcements agencies such as police, courts, and prisons. These records clearly reflect the amount of contact with the judicial system and the number of arrests for violent activity of the subjects. However, they are also only the 'tip of the iceberg' of the real number of offences due mainly to the under-reporting of violent acts by the victims and systematic biases in the police and criminal justice system (Moffitt et al., 1994). Moreover, given the legal nature of the official authorities, the records maintained by these institutions are related to acts offensive to the judicial order of the country, which are defined as crime and subject to punishment by the legal authorities. Consequently, more trivial acts such as making fun of someone, or threatening to hit someone may be considered too trivial to be charged and recorded. Thus, it is thought that official records seriously underestimate the volume of aggressive behaviour, violent or not, failing to distinguish accurately between those who are and are not involved in such behaviour (Farrington and Loeber, 2000). In addition, using such data is not only problematic for prevalence, but also for the investigation of risk factors, for there may be a systematic lack of information about individual, family and neighbourhood variables when data are simply collected for administrative purposes and official statistics.

The second approach surveys people and asks them about aggressive acts that they have committed during a given period. Unlike the official records, these self-report surveys reveal aggressive behaviour that is undetected by the judicial system (Junger-Tas and Marshall, 1999). Farrington and Loeber (2000) revealed that most youths involved in aggressive behaviour are never arrested. Nevertheless, this source is influenced by the individuals' memories and their tendency to overestimate or underestimate the frequency of their behaviour depending on their individual perception. For instance, infrequent offenders may tend to report trivial events such as fighting with siblings or using the family car without permission in response to questions about 'assault' and 'auto-theft' (Moffitt et al., 1994, Huizinga and Elliott, 1986). In contrast, frequent offenders may tend to underreport their aggressive acts because they are afraid to be denounced and sentenced (Junger-Tas and Marshall, 1999). Despite these limitations, it is generally accepted that self-reporting data provides the most accurate picture of the true number of aggressive acts committed (Tremblay, 2000, Huizinga and Elliott, 1986, Raudenbush et al., 2003), and that it more faithfully reflects actual behaviour than official statistics.

Being aware of the limitations and coverage level of both approaches, the present study uses self-reported data to measure individual level of aggressive behaviour. Importantly, this source allows data to be obtained on a wide range of behaviours including severe aggressive behaviour –referring to acts that involve breaking the law such as theft, burglary and robbery–, and non-severe aggressive behaviour –referring to acts that do not include violent acts, such as threatening or making fun of someone. This separation between severe and non-severe aggressive behaviour allows an assessment of what factors are specific to violent forms of aggressive behaviour, as well as what factors are specific to less severe forms of aggressive behaviour. Moreover, self–reported data permit the collection of more extensive and detailed information for analysing aggressive behaviour from the perspective of the individual, since they can readily be supplemented by other useful survey information on family, peers, school and neighbourhood (Raudenbush et al., 2003).

Theorising neighbourhood effects

The terms 'neighbourhood' and 'community' have been used to refer to a person's immediate residential environment. The definition of these geographic areas can be based on population characteristics, administrative boundaries, people's perceptions or on the processes through which the area effect is hypothesized to operate (Diez Roux, 2001). The term 'neighbourhood effects' involves two distinct aspects: *structural* and *social*. Structural characteristics refer to the physical environment resulting from the day-to-day life of individuals as well as the natural environment of the place. They are measured through socio-demographic characteristics of communities such as poverty, family structure, unemployment and the availability of neighbourhood resources such as education, employment, transportation, health care provision, grocery shopping and recreational services (Mrug and Windle, 2009). Social characteristics refers to the social-organizational processes or collective aspects of community life that may influence resident behaviours (Diez-Roux, 2007) such as networks, social control, social cohesion, norms of social support, perceptions of violence and collective efficacy (Sampson et al., 1997, Raudenbush and Sampson, 1999a).

Despite strong theoretical arguments that neighbourhood variables are important determinants of adolescent aggressive behaviour, neighbourhood influences have been studied far less frequently than individual, family and peer characteristics. Moreover, the available literature is inconclusive not only about the mechanisms or processes through which structural, social and individual characteristics may jointly influence such behaviour (Diez Roux, 2001), but also about the potential interactions between neighbourhoods conditions and individual characteristics shaping aggressive behaviour (Kubrin and Weitzer, 2003).

In general, the literature identifies two mechanisms that may lead to the development and maintenance of aggressive behaviour: *compositional* and *contextual*. The compositional explanation suggests that the observed differences in aggressive behaviour between communities is explained by the differences among the individuals who live there, while the contextual mechanism refers to the neighbourhood characteristics themselves, over and above the individual characteristics, that affect individual behaviour. In this section, these mechanisms are briefly outlined and are classified in proximate factors (compositional model) and distal factors (wider neighbourhood context).

Proximate causal mechanisms: compositional factors.

The compositional explanation asserts that certain types of individuals are concentrated in particular places (Government of Canada and Social Development, 1998). Therefore, when their personal and family characteristics are highly related to aggressive behaviour, this may explain why the prevalence of aggressive behaviour in that place is high. Consequently, such adolescents would be aggressive wherever they live, and the neighbourhood itself would not have an 'additional' effect on their likelihood of aggressive behaviour (Ecob and Macintyre, 2000).

The individual socioeconomic and demographic characteristics that systematically correlate with individual adolescent aggressive behaviour (and that therefore may account for neighbourhood differences) have been well investigated. For example, gender is considered the most important factor. Consistently, literature has found that males are at increased risk of aggressive behaviour, in particular of the more severe types (Farrington and Loeber, 2000, Loeber, 1990). Age is another important predictor, since most of the manifestations appear in the early childhood and tend to decrease during early adulthood but reach a peak in the teenage years (National Youth Violence Prevention Resource, 2002). In the main however, sex and age are unlikely to be strong compositional influences as neighbourhoods are unlikely to be systematically different in terms of these variables. In contrast, family variables are potentially important compositional constructs. The family environment, for example is the setting where adolescents learn and follow behaviour models, therefore, it is an important precursor of aggressive behaviour. Aggressive families tend to be characterized as being single-parent, with low economic status and antecedents of unemployment and criminality. They also are more likely to utilize inconsistent and severe upbringing strategies, as well as to offer low monitoring of adolescent activities, and to ignore prosocial behaviours (Ghate and Hazel, 2002). Within these environments, adolescents are also more exposed to domestic violence, both as victims and as witnesses, which has also been demonstrated to increase aggressive behaviour significantly. These stressful family situations may lead adolescents to be more susceptible to associate with other peers with similar family situations who also tend to be engaged in deviant and delinquent activities (Farrington and West, 1993, Loeber, 1990, Lowry et al., 1995). Moreover, studies have also reported that parents overwhelmed by economic, family or health problems are significantly more frequent among delinquent populations (Klevens and Roca, 1999).

Adolescents with one or a combination of the above characteristics tend to live in high-poverty neighbourhoods because of restrictions on their families in the choice of dwelling imposed by financial problems and the workings of the local housing market (Macintyre et al., 2002). Consequently, differences in aggressive behaviour between neighbourhoods may be explained by the clustering of similar types of adolescents and families in certain neighbourhoods rather than by the characteristics of the neighbourhood itself; this is the essence of the compositional argument.

Distal Causal mechanisms: contextual factors.

The *contextual* explanation is not a single concept and five broad models of potential contextual mechanisms can be recognized: structural, collective organization, institutional, epidemic or contagion, and parenting practices, peer affiliations and neighbourhood social network (Brooks-Gunn et al., 1997, Ingoldsby and Shaw, 2002). Each is now discussed in turn.

Structural conditions

The *structural* model emphasizes the role of physical neighbourhood conditions in which social life and individual development occurs, this includes neighbourhood disorder, poverty, ethnic heterogeneity, unemployment, lack of managerial and professional workers, family disruption and residential instability. Neighbourhoods having these characteristics are commonly described as *deprived.* This model is mainly rooted in the 'Broken Window Theory' proposed by Kelling and Wilson (1982) and in the 'Social Disorganization Theory' proposed by Shaw and Mckay (1942, , 1969). The former argues that physically broken and socially disorganized neighbourhoods appear to be unfriendly and uncared for by residents and therefore act as a magnet to delinquent behaviour and crime. Manifestations of neighbourhood disorder (damaged or boarded up homes and buildings, graffiti and vandalism, loitering or soliciting , and disorderly conduct by people in the area) encourages further incivility, indicating to residents and other passers-by that residents are indifferent to what happens in their neighbourhood. Consequently, adolescents residing in such neighbourhoods may also assume that it is an area of lawlessness where their behaviour is not monitored and controlled.

The central theme of the Social Disorganization Theory is based on the observation by Shaw and McKay (1942, , 1969) that neighbourhoods with high rates of aggressive behaviour used to be neighbourhoods with more concentrated disadvantage, residential turnover and ethnic heterogeneity. They also discovered that these high rates of aggressive behaviour persisted in such neighbourhoods over many years despite changes in the racial and ethnic composition of the population. This observation suggested that these neighbourhood characteristics themselves contribute to and maintain neighbourhood differences, and that structural neighbourhood characteristics have predictive power over and above individual factors (Ecob and Macintyre, 2000, Brooks-Gunn et al., 1997). According to Shaw and McKay, poor neighbourhood structural conditions provide room for individuals with both conventional and unconventional values, beliefs and behaviours; thus, adolescents living in those neighbourhoods are clustered together with those conventional and non-conventional or criminal tendency groups. Adolescents living in disadvantaged conditions may be more likely to join to delinquent groups and to approve or justify their behaviour.

Collective or socialization

This model also brings into play the concept of the Social Disorganization Theory, however it argues that structural neighbourhood conditions are more likely to have an indirect effect on adolescents aggressive behaviour than a direct effect. This model argues that bad structural neighbourhood conditions affect adolescent aggressive behaviour by affecting social organization within the neighbourhood (Cattarello, 2000, Shaw and McKay, 1969). Neighbourhood characteristics such as poverty, disorder, ethnic heterogeneity and population mobility may decrease communication and increase anonymity among neighbour residents which prevents them establishing relationships with one another. In such communities, neighbourhood residents are less likely to be positive and trusting toward their neighbours, to look out for one another, to intervene against a neighbourhood threat, to build community norms, shared values, mutual trust and the willingness to regulate and properly control adolescent behaviour (Sampson et al., 1997, Kohen et al., 2008). This lack of social cohesion will in turn reduce neighbourhood capacity for formal and informal social control, which in consequence will allow the unsupervised adolescents to be free to roam streets in groups, creating increased behavioural risk such as antisocial behaviour (Sampson et al., 1997, Kohen et al., 2008).

Community resources

The institutional model posits that neighbourhood resources affect adolescent behaviour through the access to stimulating learning and social environments (Kroneman et al., 2004). The presence of neighbourhood institutional resources have been studied in the form of availability, quality, quantity and accessibility of schools, police, libraries, health care, family support centres and organized social and recreational activities that are available within the neighbourhood (Brooks-Gunn et al., 1997). According to the supporters of this model, the quality, quantity and diversity of institutions promotes the opportunity to access education and employment opportunities, public utilities and community services, which in turn affects adolescents' capacity to develop their personal resources (human or financial) and to discover their desires and potential. This may, in turn, influence the choices that adolescents make and their behaviour (Wikstrom and Sampson, 2003, Molnar et al., 2008).

Epidemic or contagious process

This theory focuses on the spread of deviant behaviour due to the exposure to a violent setting. When adolescents are frequently likely to witness violent acts and aggressive relationships among family members and neighbours, they may create a positive evaluation of such behaviour and come to accept them as a standard problem-solving skill (Coster et al., 2006, Brooks-Gunn et al., 1997). The result is that aggressive behaviour is seen as a norm and is copied. In addition, adolescents living in these criminogenic settings are at the highest risk for being targets of violence; therefore, they may adopt a hyper-vigilant attitude towards hostile cues which, in turn, may also result in higher levels of aggressive behaviour (Colder et al., 2000).

In addition, a violent setting may to some extent determine the quality of neighbourhood peers which are said to transmit epidemically a number of risk behaviours, including drug, alcohol use, antisocial behaviour and contact with gang members (Rankin and Quane, 2002). According to Ingram *et al.* (2007) adolescents learn aggressive behaviours through interaction with their peers, copying behaviours that seems to be socially accepted. Consequently, if these behaviours favour deviant and delinquent activities, adolescents will tend to engage in the same behaviours as their peers.

Integrating theories: parenting practices, peer affiliations and neighbourhood social network model

It has become widely recognized that aggressive behaviour has multiple and interacting causes and that different chains, involving several different links or paths, may better explain adolescent aggressive behaviour (Lahey et al., 2003). Supporting this, Ingoldsby and Shaw (2002) integrate the mechanisms explained above to emphasize that structural community characteristics influence adolescent aggressive behaviour indirectly rather than directly, by influencing the quality of individual development, family life and friend's affiliations.

To support this, previous investigations have discussed how dangerous or highly physical and socially disorganized neighbourhoods may increase parental supervision and monitoring in order to protect their children and their exposure to negative models (Rankin and Quane, 2002). Conversely, this kind of environment may cause parental emotional distress which may also interfere with effective parenting, leading parents to be intolerant and to adopt punitive and restrictive parenting practices in order to protect their child. This greater level of parental stress and harsher discipline, leads adolescents to be more susceptible to negative peer influences. As described by the contagion theory, disadvantage communities tend to concentrate socially disadvantaged adolescents who show non-conventional attitudes and socially unaccepted behaviour that can be copied from other peers.

Previous empirical research on neighbourhood effects

The diverse theories discussed above have provided the background to a range of empirical studies, although it is rare for the full range of explanations to be evaluated simultaneously. This section presents the results of a substantial literature review on aggressive behaviour and neighbourhood characteristics. This search was undertaken between March and November 2011 using the electronic databases METALIB, MEDLINE, SPRINGERLINK, and WEB OF SCIENCE databases as well as Google. The following Medical Subject Headings (MeSH) key terms were used: aggressive behaviour, anti-social behaviour, delinquency, neighbourhood and context. The search found 47 scientific publications, in the format of journal articles, papers, conference presentations and dissertations. They are listed in Appendix 1. Most of these studies are undertaken in United States (37) with only 9 in Europe and 1 in Africa. No such study has been undertaken in Colombia, nor indeed in Latin-American. These studies are now reviewed in detail for both their substantive findings and for methodological approaches.

The overwhelming majority (46 out of 47) found strong, statistically significant overall, direct or indirect associations between neighbourhood conditions and adolescent aggressive behaviour over and above the effect of individual level characteristics. That is, there is evidence from more than a compositional explanation. Kalff *et al.* (2001) for example, analyse cross-sectional data from 734 children residing in 36 Dutch neighbourhoods and found that children living in the intermediate and most deprived neighbourhoods had significantly more behaviour problems than children living in the least deprived neighbourhoods. Also in the Netherlands, the study of Schneiders and colleagues (2003) provided support for this independent neighbourhood effect. In their study, the authors analyzed data from 1,836 adolescents interviewed twice at ages 10 and 13 to examine the effect of neighbourhood socioeconomic disadvantage on internalizing problems (measures of withdrawal, somatic complains and anxiety/depression) and externalizing problems (measures of delinquency and aggression). According to their findings, neighbourhood disadvantage is not only associated with more young emotional and aggression problems, but also contributes to increases in the total score of behavioural problems over time.

More recently, Karriker-Jaffe *et al.* (2009) analysed data derived from the Context of Adolescent Substance Use Study, a longitudinal study carried out in North Carolina (US). By using data from 5,118 adolescents aged on average 13 years old residing in 128 rural neighbourhoods, the authors investigated the direct and moderated influences of neighbourhood deprivation on trajectories of aggression (measures of fighting, hitting/slapping, and threatening with or without weapon) from ages 11 to 18, as well as its indirect effect through social organization and sex differences. Results from the multilevel analysis demonstrate that, at all ages, boys and girls living in more disadvantaged areas perpetrate more aggression than boys and girls in less disadvantaged areas. It is also found that the social organization of neighbourhoods does not buffer the negative effect of neighbourhood disadvantage for either girls or boys. Similarly, Coster and *et al.* (2006) using data related to 11,207 adolescents from the National Longitudinal Study of Adolescent Health in the US, find that community disadvantage has a significant effect on serious violent delinquency (measured as serious fight, threat, use of a weapon, hurt someone badly and shot someone) that is beyond the effects of the individual-level variables. In an earlier analysis of data from this same longitudinal study, Cleveland (2003) also support these results. By using data from the first wave related to 2,342 monozygotic twins, dizygotic twins, full-sibling, and half-sibling pairs, the author examines differences in genetic and environmental influences on adolescent aggression (measures of physical fight, carrying a weapon, using a weapon/knife) across adequate and disadvantaged neighbourhoods. In his results, the author reports that, for both sexes, adolescents residing within disadvantaged neighbourhoods have significantly higher probability of aggression than those adolescents residing in better-off neighbourhoods. Moreover, Cleveland (2003) also observes that the protective effect of effective parenting practices on adolescent aggression is stronger in high deprived neighbourhoods than in adequate ones.

In Canada, neighbourhood effects are also found by Romano and colleagues (2005) when analysing data from the National Longitudinal Survey of Children and Youth. The authors examined the independent effects of individual, family and neighbourhood-level predictors on young physical aggression (measures of involvement in fight, kick, bites or hits on other children, etc.) and found that youths living in neighbourhoods perceived by the mothers as experiencing more problems, have higher levels of physical aggression. Similar results are found in an Edinburgh cohort study where the relationship between criminal offending and neighbourhood instability, economic deprivation, street crime, community satisfaction, community safety, collective efficacy, incivilities and cannabis acceptance is explored (McVie et al., 2006). Results reported by the authors demonstrate that only concentrated deprivation has an independent effect on the probability of offending behaviour over and above the effect of individual-level measures. In contrast, using data from the same cohort, the authors draw a different conclusion regarding poverty when exploring the role of these neighbourhood conditions on adolescents property offending trajectories (early onset desisters, late on-setter and chronic offenders) (McVie and Norris, 2006). In this second study, the authors do not find a significant relationship between neighbourhood economic deprivation and trajectories of property offending. However, lack of neighbourhood informal social control significantly predicts higher levels of offending behaviour in those classified as early onset and chronic property offenders. Similarly, high residential turnover and neighbourhood migration strongly influence the probability of offending for those chronic offenders.

The multilevel analysis of Hoffmann (2006) used longitudinal data from the National Educational Longitudinal Study (NELS) in the USA to explore the independent effect of neighbourhood percent of female-headed households, jobless males, poverty and racial segregation on adolescent delinquency (measured by involvement in fighting, getting suspended or expelled from school, and being arrested by the police). Adjusted analysis showed that adolescents living in communities with more male joblessness, a higher percentage of female-headed households and more poverty are more likely than adolescents living elsewhere to be involved in delinquent behaviour. The author also found that the impact of stressful life events on delinquency is stronger in communities with a higher proportion of jobless males. Similar conclusions are reached when the analyses is restricted to adolescents living only in urban areas.

Experimental designs have been also used to provide further empirical support for the link between neighbourhood conditions and adolescent aggression. By using families registered under public housing schemes in Baltimore, Ludwing and colleagues (2001) randomly assigned the families to three groups: i) an experimental group which received Section 8 vouchers and special assistance to move from low-income housing projects to low-poverty neighbourhoods, ii) a control group which received vouchers to move into private housing of their choice, and iii) another control group which did not receive vouchers and remained in public housing. A comparison of the offender records of adolescent males belonging to the participant families show that male adolescents in the experimental group are significantly less likely to be arrested for violent crimes than their counterparts who stayed in public housing. Using data from the same experimental study, Kling and colleagues (2005) estimate neighbourhood effects on crime and delinquency among females and males aged 15 to 25 years at the end of 2001. The authors report significant gender differences in the relationship between neighbourhood conditions and juvenile crime. According to the results, in comparison with the control group, females in the experimental group are less likely to be arrested for violent and property crime. However, males are less likely to be arrested for violent crime but more likely be arrested for property crimes.

There are other neighbourhood characteristics apart from socio-economic status that have been found to affect adolescents' risk of aggression. For example, Anderson (2002) investigated the role of the proportion of single-parent families on three measures of adolescent delinquency (status offenses, property crimes and person crimes). The authors found that over and above the individual-level effect, a higher proportion of single-parent families is significantly related to the higher risk for person crimes and marginally for status and property offenses. Recently, Jennings and colleagues (2010) also investigated the simultaneous effect of neighbourhood problems on physical aggression (measures of involvement in hitting or beating up, physical fight, threats, etc.). By using a sample of 5,812 adolescents aged 12 to 14 from the Project Northland Chicago, the authors found that neighbourhood problems have a significant effect on adolescent physical aggression, which is maintained once individual-level risk factors and demographics are incorporated into the model.

A wider range of neighbourhood conditions are examined by Frank, Cerdá and Rendón (2007) on a sample of 890 adolescent aged 12 to 17 in Los Angeles, California. The authors evaluate the impact of neighbourhood poverty, concentration of Latinos, African-Americans and immigrants, neighbourhood social cohesion, social organization, informal social control and collective efficacy on adolescent delinquent behaviour (measures of sexual activity, gang membership, ran away from home and gun ownership). By using hierarchical modelling, the authors found that residences in areas with higher levels than the city-average of Latinos significantly affect individual delinquent behaviour. Although the authors do not find a significant direct relationship with neighbourhood poverty or collective efficacy, they report significant cross-level interactions. Among these, the authors found that Latinos living in neighbourhoods with a high-concentration of Latinos have three times higher odds of delinquency than those adolescent Latinos living in neighbourhoods with a lower concentration. They also observe that in neighbourhoods with high levels of collective efficacy, third-generation Latinos have significantly lower odds of delinquent behaviour than their group of reference residing in communities with lower levels of neighbourhood social organization.

A set of relevant studies have been also carried out using data from the Project of Human Development in Chicago Neighbourhoods (PHDCN), which is a longitudinal study designed specifically to investigate neighbourhood contextual effects on individual development. One of them was undertaken by Zimmerman and Messner (2010) who investigated the influence of neighbourhood concentrated disadvantage, immigrant concentration, and residential instability on adolescent violent crime (measures of hitting someone, using a weapon; throwing objects, carrying a weapon; setting fire to properties, stealing and participating in a gang fight), as well as the gender gap across neighbourhoods. The results of the analyses indicate that, net of the individual control variables, the only neighbourhood variable related to adolescent violent crime is concentrated disadvantage. According to the results, increases in levels of neighbourhood concentrated disadvantage are associated with higher adolescent violent crime. The authors also report that the gender gap in violent crime decreases as levels of neighbourhood disadvantage increase. In a second study, Zimmerman (2010) used data of the first and second wave to examine if the influence of impulsivity for violent crime (defined as in the previous study) and property crime (measures of breaking and entering, stealing from a store/car and buying/selling stolen goods) differed as a function of the neighbourhood context. His results reveal that in neighbourhoods with higher levels of socioeconomic status and collective efficacy, and lower levels of criminogenic behaviour settings and moral/legal cynicism, the effects of impulsivity on adolescent violent and property offending are significantly stronger.

Also researching in Chicago, Cheong and Raudenbush (2000) used data from 2,177 children aged 9-15 residing in 79 urban neighbourhoods. The authors demonstrate significant neighbourhood effects on externalizing behaviour problems (measures of aggression and delinquency). According to the model results, the probability of both juvenile aggression and delinquency is significantly higher in neighbourhoods characterized by high concentrated disadvantage. In addition, it is found that for both types of externalizing behaviour, this effect is particularly important at age 12 and much smaller at ages 9 and 15.

Also deriving data from the PHDCN, Molnar *et al.* (2008) investigated the role of neighbourhood-level resources on levels of juvenile aggression and delinquency among 2,226 youths aged 9–15 years residing in 80 Chicago neighbourhoods. They find that living in neighbourhoods with high concentration of organizations and services conferred a protection from engaging in aggression. They also report that in neighbourhoods with lower than average levels of community resources, influences with prosocial peers confer a protective effect of 10% on the risk of aggression. However, in neighbourhoods with higher than the average levels of community resources, the protective effect is 30%. The authors also emphasize the protective effects of family support and availability of non-parental mentors, which are significantly associated with lower odds of aggression in neighbourhoods with high levels of social networks, resources and institutions.

Another relevant longitudinal study used to investigate both cross-sectional and longitudinally the relationship of neighbourhood conditions on adolescent aggressive behaviour is the male sample of the Pittsburgh Youth Study (PYS). Peeples and Loeber (1994) analysed data from 506 adolescents aged 13 years old residing in 88 Pittsburgh neighbourhoods. The authors assess the effect of residing in underclass neighbourhoods on the propensity of: delinquency seriousness, frequency of serious delinquency, and total frequency of delinquency (measures of involvement in theft, vandalism, or fraud, carrying weapons, gang-fighting, forced sex or selling drugs). Results show that, after accounting for individual and family predictors, residence in underclass neighbourhoods is strongly related to all forms of adolescent delinquency. The authors also find that the relationship between race and delinquency is only significant in underclass neighbourhoods.

More recently, Beyers and colleagues (2001) analyzed data from 420 male adolescents aging 13 to 19 who resided in the 88 Pittsburgh neighbourhoods and report that adolescents living in low-socioeconomic neighbourhoods are more likely to commit acts of violent delinquency (measures of attacking someone with a weapon, physically hurting or threatening to have sex and having sex with someone against their will). These adolescents are also more likely to be charged with a violence crime.

Wikstrom and Loeber (2000) researched children aged 10 to 13 years-old and constructed a risk/protective score based on six individual and family variables: hyperactivity/impulsivity/attention problems, lack of guilt, poor supervision, low school motivation, peer delinquency and attitudes toward antisocial behaviour. This score is then used to examine the prevalence and age of onset of serious juvenile offending (measures of delinquency acts) in four types of socio-economic neighbourhood context: disadvantaged public housing areas, disadvantaged non-public housing areas, advantaged and middle-range. Their findings indicate that neighbourhood socio-economic context does not have a direct impact on the early onset of serious offending of those males scoring high on risk factors. However, for those males who scored high on individual protective factors or who have a balanced mix of protective and risk factors, the neighbourhood socio-economic context has a significant impact on the late onset of offending. In a related study also using also the PYS data, Ingoldsby *et al.* (2006) examined the effect of neighbourhood disadvantage and presence of deviant peers within the neighbourhood on early starting male antisocial pathways (measures of fighting, stealing and lying/cheating) at ages 5 to 11. According to their results, neighbourhood disadvantage set children off at risk for early starting trajectories, while neighbourhoods with high presence of deviant peers significantly influence levels of antisocial behaviour over middle childhood.

Similar to the analysis of Zimmerman (2010), Lynam and colleagues (2000) used PYS data related to 430 boys aged 13 years residing in 90 neighbourhoods to explore significant cross-level interactions between impulsivity and neighbourhood poverty on five delinquency scales: status offences (running away, truancy), vice (drunk, selling drugs), theft (shoplifting, joyriding), violence (attack with a weapon, rape) and the total number of acts committed. Adjusted results showed that neighbourhood poverty has only a main effect on violent crime, indicating that boys in poorest neighbourhoods engage in more types of violent crime. The authors also report that all the positive effects of impulsivity on the delinquency scales are strengthened in impoverished neighbourhoods. The authors conclude that for impulsive boys residing poor neighbourhoods there is a greater risk of delinquency.

In discussing the mechanisms through which the effect of structural neighbourhood conditions produces aggressive behaviour, the empirical evidence confirms the importance of the social organization of the neighbourhood, peer groups and parenting behaviour as intermediate factors. In the late eighties, Simcha-Fagan and Schwartz (1986), for example, reported such indirect effects. By using a sample of 553 young male adolescents from 12 New York city neighbourhoods, the authors find that adolescents living in neighbourhoods with lower organizational participation and higher disorder and criminal subculture are significantly at higher risk of the three types of delinquency: self-reported delinquency (measures of truancy, suspended or expelled from school, graffiti, running away from home), officially recorded delinquency (ever-officially charged) and severe self-reported delinquency (measures of assault, robbery, burglary and arson). In addition, the authors also conclude that this effect is mainly indirect, operating through the socialization processes within the neighbourhood and the family. More recently, Obewittler (2004) also reaches similar conclusions when analyzing self-reported data from 2,500 German adolescents between 13 and 16 years old residing in 61 neighbourhoods. The author reports positive direct effects on the probability of serious offending (measures of violence and serious property offenses) of neighbourhood disadvantage and violence tolerance, and a negative direct effect of intergenerational social ties. Most of the effect of neighbourhood disadvantage is explained by levels of social organization, which in turn reduce adolescent offending. Going further, the author also observes that the effect of the individual-level influence of violence tolerance on juvenile offending is less pronounced in neighbourhoods with higher levels of effective social organization. Cattarello (2000) studied 1,488 adolescents aged 14-15 years residing in 39 census tracts in Kentucky (USA), finding that neighbourhood social disorganization significantly influences levels of juvenile delinquency (measured through the use of marijuana), but that such effects are fully explained by the strong influence of neighbourhood disorganization on friends' use of marijuana. Adolescents living in more socially disorganized neighbourhoods are more likely to associate with friends who use marijuana in comparison with adolescents living in less socially disorganized neighbourhoods.

By using data derived from the National Longitudinal Study of Adolescent Health in the USA, Haynie and colleagues (2006) explore a sample of 12,747 adolescents nested within 2,449 census tracts. The authors found that the significant effects of disadvantaged neighbourhoods and low immigrant concentration on adolescent violence are fully explained by the increased risk of association with violent and academically unmotivated friends within these neighbourhoods. It is also reported that although residential instability is not directly related to adolescent violence, it is indirectly related via its influence on violent peers.

Using data from the Canadian National Longitudinal study, Kohen and Leventhal (2008) examine the mechanisms through which neighbourhood socioeconomic conditions impact on behavioural outcomes of young children (hyperactivity/inattention, prosocial behaviour, emotional disorder/anxiety, aggression, indirect aggression and property offenses). They find that neighbourhood disadvantage has no direct effect on behaviour problems; however, it does have an indirect effect via its impact on neighbourhood social processes. According to their path model, neighbourhood structural disadvantage reduces neighbourhood cohesion, which in turn leads to inappropriate family functioning and higher maternal depression. These family conditions are then related to less consistent and more punitive parenting practices, which finally results in worse child behaviour. Similar conclusions are drawn by Rankin and Quane (2002) in their study of 636 youths aged 11-16 years old residing in 59 Chicago neighbourhoods. On the basis of multilevel analysis, their results provide support for a substantial indirect effect on problem behaviour (serious delinquency) operating via collective efficacy, parenting and peer groups. According to the results, neighbourhood collective efficacy has a strong effect on the quality of friends. Residing in cohesive neighbourhoods leads to positive peer attachments. Similarly, youth residing in neighbourhoods with higher levels of disadvantage have marginally less prosocial friends. The authors also test cross-level interactions finding that neighbourhood social organization moderates the effect of parenting on youth behaviour. In high collective efficacy neighbourhoods, monitoring has little effect on adolescent problem behaviour, whereas in neighbourhoods where collective efficacy is low, monitoring has a stronger effect.

Chung and Steinber (2006) report that weak neighbourhood social organization is indirectly related to delinquency through its association with parenting behaviour and peer deviance, and that a focus on just one of these interacting micro-systems can lead to oversimplified models of risk for juvenile offending. In the longitudinal study of Tolan and *et al.* (2003) in Chicago neighbourhoods, the authors explore the processes by which community characteristics impact on youth involvement in violence (measured by assault, sexual assault and murder). According to their results, community structural characteristics such as concentrated poverty, low economic development, and high crime levels affect community social processes (neighbourliness and extent of problems) as well as the strategies of parental supervision. In addition, it is observed that parenting practices significantly predict gang membership which in turn influences peer violence, a factor found to directly affect individual violence.

Furthermore, Chung and Steinberg (2006) examined the effect of neighbourhood social and structural conditions, parenting practices and peer affiliations on delinquency among a group of serious adolescent offenders. They show that social rather than the structural conditions of the neighbourhood indirectly influence the probability of delinquency via its effect on parenting behaviour and peer associations. This pathway is also discussed by Simons *et al.* (1996) when using data from a sample of 207 female-head families with adolescents sons residing in 104 neighbourhoods of Iowa (USA). Results from the path analysis show that for boys, none of the neighbourhood constructs are directly related to adolescent conduct problems (measures of skipping school, fighting, stealing, physical aggression, saying nasty things); however, community disadvantage increases the probability of conduct problems by affecting parenting and increasing involvement with deviant peers. For girls, the proportion of single parents contributes both directly and indirectly to conduct problems, the latter explained by an increased probability of engaging with deviant peers.

More recently, the same lead author and other colleagues (Simons et al., 2005) investigated the effect of neighbourhood collective efficacy, social cohesion, concentrated disadvantage and residential instability on adolescent affiliation with deviant peers and delinquency (measures of shoplifting, physical assault, lying, setting fires, cruelty to animals, vandalism, burglary and robbery). By using data from two different waves of data from the Family and Community Health Study undertaken in Georgia and Iowa (USA), the authors find that only collective efficacy significantly increased the probability of delinquency. Additionally, the authors reported that the protective effect of authoritative parenting on delinquent behaviour is enhanced in communities with high collective efficacy.

In contrast to these studies, Dahlback (1996) in Stockholm failed to detect such direct associations. In his analysis, the author used data from 7,719 males to test the influence of area of residence on individual criminality (measured as number of violent crimes, theft, fraud, vandalism, traffic violations and drug violations). He finds that the location of residence had neither a cross-sectional nor a longitudinal relationship with individual criminality. Bernburg and Thorlindsson (2007) also fail to find evidence of a significant impact of community socioeconomic status and urban location on individual delinquency when analyzing data from 6,458 students aged 15 and 16 in Iceland. However, this study finds that communities characterized by high levels of social instability are strongly associated with higher levels of adolescent delinquency.

A key issue that emerges from the reading of the available literature is that, although there is strong evidence to support the idea that neighbourhoods are important settings to impact directly or indirectly adolescent aggressive behaviour, their importance in terms of the amount of unexplained variance is small when compared to the individual and family levels. Moreover, the typical neighbourhood constructs used to explain such variation seem to add little to the explanation of the neighbourhood differences. In general, the studies described above show that, after taking individual and family characteristics into account, the variance explained by the neighbourhood-level conditions is substantially reduced. This indicates that not only is most of the variation in adolescent problem behaviour within the neighbourhood, but that a substantial proportion of the between-neighbourhood variation is due to the neighbourhood concentration of families and adolescents with similar characteristics and not to the characteristics of the neighbourhood itself (Oberwittler, 2004).

This observation is discussed in Levental and Brooks-Gunn (2000), who highlight that in most of the reviewed studies the neighbourhood effects account for only about 5% of the total variance after controlling for demographic and family-level variables. Thus, Cheong and Raudenbush (2000) as well as Bernburg and Thorlindsson (2007) report that the remaining neighbourhood-level variance for delinquency after adjustment by baseline individual variables is about 3%. Comparable values are reported by Obewittler (2004) in his study of the German sample, where the estimated percentage at the area level for serious offending is 4.2%, which reduces by about half once socio-demographic characteristics are adjusted for. Similarly, Zimmerman (2010) reported that around 4.4% of the variation of adolescent violent crime lies between-neighbourhoods, which is reduced to 1.5% after the inclusion of person-level covariates. Furthermore, Rankin and Quane (2002) also demonstrated an estimated neighbourhood variance of 4%, of which 75% was explained by individual-level factors, concluding that the neighbourhood differences in problem behaviour are mainly due to the clustering of individual-level factors. A similar conclusion is drawn by Simcha-Fagan and Schwartz (1986) who report that the amounts of neighbourhood variation associated with three types of delinquency range only from 2% to 4% after controlling for individual-level characteristics. In the multilevel analysis of Hoffmann (2006) and the one undertaken by Simon and colleagues (2005), the authors reported that the neighbourhood variation of adolescent delinquency across neighbourhoods is around 5%. More recently, Jennings and colleagues (2010) reported a significant neighbourhood-level variation of adolescent physical aggression ranging between 5% to 10% during the three years of the study. Karriker-Jaffe (2009) found that for girls the proportion of variance of adolescents aggression lying at the neighbourhood level is 7.6% while for boys, it is zero. By using data for 12-17 year old adolescents from 11 cities in the Netherlands, Weijters *et al.* (2007) found significant differences between neighbourhoods of 0.3%, but more importantly between cities of 4.6%.

Nonetheless, although most of the neighbourhood-level variance seems to be explained by the socio-demographic composition of respondents, the studies highlighted above have given evidence not only of an independent predictive power of neighbourhood conditions beyond individual characteristics, but also about their role in moderating the magnitude and direction of the effect of individual predictors. That is, even in cases where the neighbourhood-level variance is estimated as zero, it is found that the associations between individual risk factors and adolescent aggressive behaviour is dependent on the context in which those risks are experienced.

In summary, although relatively few in comparison to the study of individual risk factors, the available empirical studies demonstrate the effects of compositional and contextual characteristics on aggressive behaviour and these findings have contributed significantly to the understanding of how aggressive behaviour is established and maintained. However, no quantitative research has yet demonstrated this issue in a developing country setting.

Methodological problems in studying neighbourhood effects

A thorough review of the existing literature has identified four important methodological challenges that face the quantitative analysis of neighbourhood effects. Here each is considered in turn and there is a discussion of how each are to be tackled in this thesis.

Multiple levels

Individuals and neighbourhoods do not lie at the same level of analysis. That is, there is conceptually a hierarchical structure in which adolescents are nested within neighbourhoods (Kalff et al., 2001, Subramanian et al., 2003). This structure commonly results in adolescents from the same neighbourhood being more similar than adolescents from different neighbourhoods (Diez Roux, 2000). Not taking account of this structure in the analysis will increase the statistical significance of the regression coefficients and underestimate their standard errors, leading to incorrect conclusions (Subramanian et al., 2003). The development of multilevel models takes account of this nested structure and provides several advantages as it permits a decomposition of the sources of variability in the outcome (between neighbourhood and between adolescents within neighbourhoods), and it leads to more precise *p*-values and confidence intervals for the estimate of the influence of individual and neighbourhood factors. The majority of the studies (28 out of 47) used this methodological approach while the others used single-level models with the potential for inferential error as well as poorer substantive analyses. For the present study, the hierarchical nature of the research problem is recognized and consequently, multilevel techniques are used in all the analytical chapters.

Measuring adolescent aggressive behaviour

As discussed earlier, data obtained from the workings of the criminal justice system have been shown to be a poor estimate of aggressive behaviour, especially for less severe aggressive behaviours. Consequently, most of the previously identified studies used some form of self-reported questionnaire, and this study does likewise. However, the majority of these studies simply aggregated different types of behaviour to provide an overall summary index, by summing the 'yes' answers into an overall score. This approach presents methodological limitations since it assumes that each question should contribute equally to the total score. Consequently, more and less severe behaviours are considered equally important in determining the score. However, *having committed a rape* cannot and should not equated with *having made fun of someone*, and this differentiation is ignored when using a summed scale. Aggressive behaviour is more properly seen as an underlying latent trait that cannot be directly measured and a methodology is required that takes multiple measures or indicators (through asking a battery of questions on specific forms of aggressive behaviour) and estimates this underlying propensity, thereby deriving a valid and reliable measure of the level and severity of the outcome of interest. Only four of the reviewed papers considered this. Consequently, as fully discussed in Chapters Three and Four, an explicit measurement model is developed, using the approach of Item Response Theory and the Rasch model, to measure individual and neighbourhood aggressive behaviour latent traits that takes account of the differential severity of the items. This methodology is another form of a multilevel model that now has different items (questions on specific forms of aggressive behaviour) nested within adolescents who are nested in neighbourhoods.

Measuring neighbourhood characteristics

The theoretically-informed neighbourhood literature has developed a range of constructs and typologies of neighbourhood conditions for the study of contextual effects. In contrast, much of the empirical literature commonly uses conveniently available data, typically census data, to both define neighbourhoods and to measure neighbourhood characteristics. Neighbourhood effect studies typically aggregate individual characteristics of the residents, or use census data to create structural neighbourhood indicators such as median income, unemployment rate, and socioeconomic composition. Although these variables can be measured with a satisfactory degree of validity and reliability, they may be relatively poor indicators of the underlying theoretical construct related to neighbourhood effects which highlight social properties which do not represent a simple aggregation of individual attributes (Bursik and Grasmick, 1996). Consequently, the use of community surveys is being increasingly used for capturing such information. Whereas, much of the analysis of community surveys has been limited to simple aggregation, but novel approaches such as multilevel confirmatory factor analysis and multilevel latent class analysis have shown significant improvements in the process of proper measurement of constructs operating at the neighbourhood level. Moreover, application of ecometrics allows researchers to assess the quality and reliability of the resultant neighbourhood scales (Leventhal and Brooks-Gunn, 2000, Sampson and Raudenbush, 1999). This ecometric approach integrates Item Response Theory into hierarchical modelling in order to develop contextual measures from community-surveys (Raudenbush and Sampson, 1999b). To date, however, few studies have used these methods, being more guided by what is available than by the theoretical considerations and methodological sophistication. In Chapter Five, social and structural neighbourhood characteristics are ecometrically estimated using data from two community surveys and other administrative sources, which are independent of the individual aggression survey.

The conceptual status of variables

An important aspect of research design is the need for a clear and theoretically justified analytical strategy. An important aspect of this is the conceptual status of variables and how they are to be incorporated into the model, whether they are evaluated as confounders, mediators or moderators of the neighbourhood effects (Victora et al., 1997). Most of the 47 studies reviewed assessed simultaneously the effect of individual and neighbourhood variables and justify their decision about the choice of their predictors based purely on statistical associations, rather than any conceptual basis for the inter-relationships between them. In addition, these studies commonly consider the coefficients of only the neighbourhood variables as the neighbourhood effects, which would underestimate the true effect of neighbourhood characteristics on aggressive behaviour by removing the effects mediated through the individual variables placed on the causal pathway (Leon, 1993). If this is the case, then the interpretation of the results may lead to incorrect conclusions. As the aim is to better theorize the mechanisms that link neighbourhood characteristics and aggressive behaviour, a conceptual model is developed which allows the proper assessment of both the direct and indirect effect of the structural and social neighbourhood conditions on aggressive behaviour. This conceptual model is based on the ecological pathway approach outlined in Chapter One and considered in more detail in Chapter Six. It is estimated using both a standard multilevel model to assess overall effects and a multilevel structural equation model for assessing indirect effects in multilevel analysis.

Conclusions

This review of the existing literature has revealed a number of studies that have undertaken research on neighbourhood effects and adolescent aggressive behaviour. However, almost of all of these have taken place in developed countries. In addition, somewhat modest results have been found and it is argued that this may be due to poor theoretical, conceptual and methodological understanding of the issues involved. These problems are addressed in the analytical chapters of this thesis by using a variety of statistical techniques to define better both individual and neighbourhood conditions as well as to estimate better their effects and the mechanisms by which neighbourhood conditions are transferred. It is hoped that, with the combination of detailed surveys, multiple sources of data, theoretical elaboration and appropriate methodology, consistent and reliable results can be obtained about the size and nature of neighbourhood effects.

Chapter 3. Measuring individual aggressive behaviour from self-reported data

This chapter is concerned with the measurement of individual aggressive behaviour. This is most appropriately conceived as one or more underlying latent traits that cannot be directly observed and measured. Self-reported questionnaires are commonly used to elicit these behaviours which are then turned into some underlying scales. A number of different methodologies are used to derive these traits and the effectiveness of a range of procedures is considered. In particular, attention is focussed on how Item Response Theory can be used to select the items that best describe the underlying trait of interest and how it can be integrated with multilevel modelling techniques to measure underlying continuous scales. This methodology is applied to a survey of adolescents in Medellin. Responses to 14 self-rated survey questions are modelled to extract the latent traits of aggressive behaviour and to evaluate the nature of the variation between individuals. This chapter is an extended one. This is because, in considering measurements models as multilevel models, it sets the analytical framework for the three subsequent analytical chapters of the thesis.

Measuring aggressive behaviour: traditional and new approaches

Self-reported instruments with multiple item scales are frequently used for measuring aggressive behaviour indicators and scoring a latent trait. Typically, they include several items with binary (Yes/No), ordinal (ranked) or count responses about the number, severity and types of aggressive behaviours that the individuals have engaged in over a period of time (Raudenbush et al., 2003, Piquero et al., 2002, Osgood et al., 2002).

A critical reading of an extensive psychometric literature (Piquero et al., 2002, López and Hidalgo, 2005, Kamata, 2001, Bond and Fox, 2007) suggests that the derivation of the underlying latent trait of aggressive behaviour should have the following desirable psychometric properties:

- *Severity of behaviour:* the ability to distinguish the more severe acts of aggressive behaviour from others;
- *Coverage*: the items should cover the full range of the latent trait so, it is possible to recognise those individuals at the extremes and in the middle;
- *Dimensionality*: refers to the requirement that items tap a single underlying construct;
- *Reliability:* refers to the extent to which a measurement instrument yields consistent, reproducible estimates of what is assumed to be an underlying true score;
- *Validity:* refers to the capacity of the scale to differentiate individuals with problems of aggressive behaviour from the rest of the community, and;
- *Adjusted by measurement error,* this property is related to the random errors of measurement related to problems in the questionnaire, problems with the interviewer or in the respondent's behaviour. if not adjusted, these errors may raise or lower the estimated latent away from the true latent trait (Fox, 2005).

Traditionally, the procedures of summing scales and standard factor analysis have been used to combine the set of aggressive behaviour items and estimate the underlying trait. However, both approaches have important methodological limitations when measuring the propensity of aggressive behaviour and particularly when evaluating their psychometric properties. In the summing strategy, all the responses to the items are counted as the total number of aggressive behaviours committed for each respondent and the sum or mean of this count is used as the individual's score of aggressive behaviour (Osgood et al., 2002). The resulting scale, if no weighting is applied, assumes that each item contributes equally to the total score. Consequently, more and less severe aggressive behaviours items are deemed as equally important in determining the score. In practice, it is common for only a small number of respondents to state that they have been engaged in the more severe behaviours. Consequently, the sum usually has a distribution that is discrete and skewed. Even for a scale with multiple items, the majority of the respondents will be at the floor of the summed scale, with small numbers of respondents at each score as the values progress up the scale (Johnson and Raudenbush, 2006). When this summed score is used in further statistical analysis, the discreteness and the lack of Normality can be problematic. Moreover, this summing approach does not take account of measurement error and does not readily cope with respondents with missing information for some items.

In the traditional factor analysis approach, a number of latent constructs are identified by combining correlated items into one or more factors. However, this method assumes that the observed variables are continuous, even when the items are scored dichotomously or polychotomously, which can result in misleading factor analysis findings (Fone et al., 2006, Glockner-Rist and Hoijtink, 2003, Kamata et al., 2008). Moreover, the importance of measurement invariance and the detection and coping with measurement error cannot be easily achieved with factor analysis (Glockner-Rist and Hoijtink, 2003). Another important limitation of these two methods is that they do not enable the researcher to extract more sophisticated and detailed information regarding the desired properties of the items and the resultant scales, especially their reliability.

Raudenbush and colleagues (Raudenbush et al., 2003), in their development of scales of criminal behaviour for Chicago adolescents, combine the concepts of the Item Response Theory (IRT) with multilevel modelling to create meaningful metrics that reflect the varying seriousness of the behaviours and that properly measure individual criminality while controlling by measurement error. In particular, they used a specific form of an IRT model known as the Rasch model to define normatively what constitutes good measurement. According to these authors, this novel approach enables the researcher to identify the set of items that better fit the model, to accurately assess how much of the latent trait an individual possesses, and to assess the reliability, validity and dimensionality of the constructs. In their study, they used binary item responses for self-reported violent behaviour (such as hitting someone, throwing objects to others, robbery, damaging property, stealing from a car/store/household member) to estimate two underlying continuous crime dimensions: violent crime and property crime. They were also able to study the correlations of the two dimensions.

Despite the considerable merits of this approach, an extensive literature search found only one additional study where an IRT model is used to evaluate the Rasch properties of the data, to identify uni-dimensional scales and subsequently to embed it into a hierarchical model to define an interval scale for individual aggressive behaviour outcomes. This study, again by Raudenbush and colleagues, analyses a cohort study which began in 1994 in Chicago urban neighbourhoods as part of the Project on Human Development in Chicago Neighbourhoods (PHDCN) (Cheong and Raudenbush, 2000). By using data from a subsample of the 1994-1997 wave of the PHDCN, the authors analysed 33 items from 2,177 children aged from 9 to 15 in 79 neighbourhoods. They calibrated two interval scales for childhood behavioural problems, namely aggression (arguing a lot, bragging, screaming a lot, threatening people, physically attacks) and delinquency (lying, cheating, truancy, skipping school, stealing, vandalism). The authors are able to analyse the items' function within each construct; to assess the dimensionality and to study simultaneously how individual and contextual factors are related to the underlying dimensions of problem behaviour. Other studies were found that estimate a multilevel Rasch model to predict the odds of engaging in aggression or violent behaviours (Zimmerman, 2010, Frank et al., 2007). However, none of these studies undertook the crucial

Rasch normative analysis to select the items with good properties that can be used to create uni-dimensional scales.

In this chapter, the analytic strategy initially proposed by Raudenbush is applied to select the items and to measure the degree of aggressiveness shown by adolescents. The analysis uses a set of items taken from a self-reported survey in Medellin-Colombia and is concerned to develop high-quality scales. The rest of this chapter is organized as follows. First, the self-reported survey, which is the basis for constructing the outcome variables, is presented. Then, the novel methodological framework that integrates IRT concepts and multilevel modelling is detailed. Next, using the set of 14 self-reported aggressive behaviour items, a sequence of latent models of growing complexity are estimated to obtain valid measures of individual aggressive behaviour.

In fact, three models are fitted to accomplish these goals:

- A two-level two-parameter model with items nested within individuals, in which there is a common latent trait across all items but each item has its own severity and discrimination. This more complex model is used to identify items that are or are not equally discriminating in terms of aggressive behaviour.
- A two-level one-parameter model (the so-called Rasch model) with items nested within individuals, in which items only differ in term of severity. This model is used to assess Rasch's properties;
- A two-level multivariate Rasch model, which retains the same structure but simultaneously models the two revealed dimensions of aggressive behaviour.

A range of procedures are deployed in the estimation and interpretation of these models. Both maximum likelihood estimation and MCMC estimation are used and the procedures of model evaluation and interpretation require a range of software environments including the writing of original macro code. The outline of the procedures is shown as a flowchart in Figure 2.

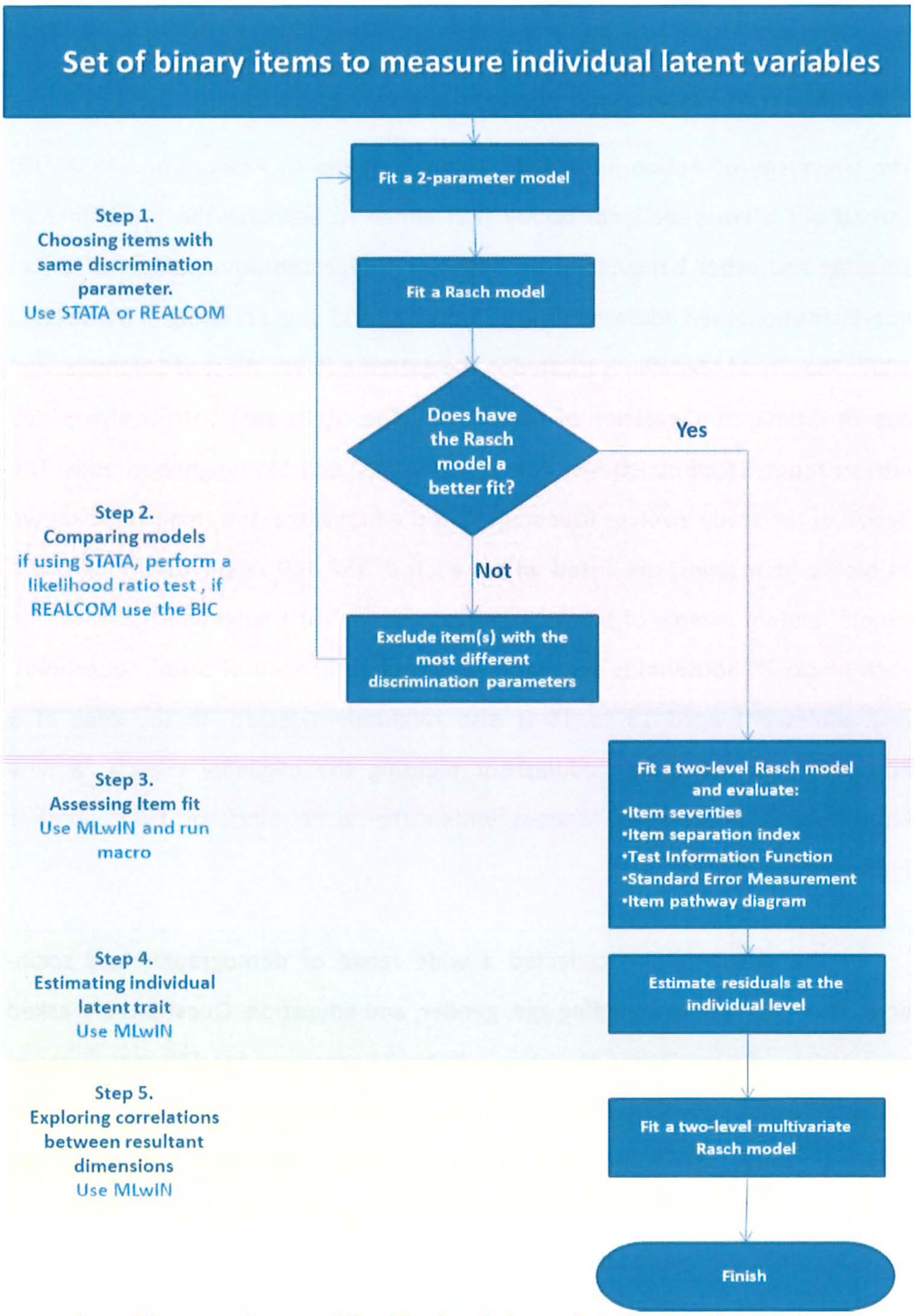


Figure 2 Steps to perform a multilevel Rasch analysis to estimate individual latent traits

The chapter concludes with a return to the desirable properties for aggressive behaviour scales outlined above, and assesses the extent these have been satisfied for the Medellin study. The next chapter extends these models to the simultaneous measurement of aggressive behaviour at both the individual and neighbourhood level. The scales developed in these two chapters will then become in effect the response variables in Chapter Six.

The Medellin adolescents survey

The University of Antioquia and the Colombian Health Association (ASSALUD) carried out a cross-sectional survey that aimed to estimate the prevalence of smoking and other behavioural problems in a representative sample of urban non-institutionalized adolescents aged from 13 to 15 years residing in Medellin in 2007. The city of Medellin is located in the extreme North West of Colombia, and has an estimated population of two million. The city is administratively divided into six zones, 16 administrative district (comunas) and 249 neighbourhoods. The design of the study involves four stages. At the first stage, the small areas known as blocks (*manzanas*) are listed within each of the 249 neighbourhoods and a simple random sample of blocks is carried out for each neighbourhood. Within each block, 25 households are randomly selected. In each of these households, one adolescent aged 13 to 15 is also randomly selected. In the case of a household not having an adolescent meeting the eligibility criteria, a new household is selected at random within the same block or from another randomly selected block.

The questionnaire collected a wide range of demographic and socio-economic information including age, gender, and education. Questions are asked on a variety of experiences as victim, witness or aggressor for different forms of violence: verbal aggression, tricks, threats, physical injuries, wounds, robberies, cheating, rapes, homicides and forced migration. For each behaviour, the adolescents are asked a Yes/No question of whether they had *ever* committed an aggressive act at home, in the school, in the neighbourhood, or in another place; and the age at which the first time it occurred. If they answer 'yes', they are additionally asked how often they had committed the aggressive behaviour acts during the last 12 months. The frequency in the last year is elicited on a scale of 1 to 5: 'Not in the last 12 months', 'One to twice', '3 to 5 times', '6 to 10 times' and, 'more than 10 times'. In total, information on 348 items are collected. In this chapter, the variables relating to being an aggressor are used. Given the relatively low frequency observed in the Likert-scales used to rate the frequency during the last year, all the items related with the lifetime experience are used in the analysis.

On completion of the survey, 1,843 adolescents had answered the questionnaire, from which 1,788 adolescents provided sufficient geographical information to allow them to be located in one of the 249 neighbourhoods in the city. Four adolescents had not answered any of the items related to being an aggressor and 98 lived in a neighbourhood to which there is no available social and structural neighbourhood information (see Chapter Five) and thus were removed from the sample. Consequently, 1,686 respondents represent the sample for the current study, who reside in 103 neighbourhoods out of the 249 in the city. In the resulting sample there is a mean of 16 adolescents in each neighbourhood. The average age of the participants in the sample is 13.4 years and 52.0% are males.

In total, the aggressive behaviour questions produced up to 105 items for each adolescent. Initial descriptive analysis of the data showed very low frequencies for some of the questions relating to having committed acts of aggressive behaviour at home and in other places. Most of the adolescents admit to committing aggressive acts at the neighbourhood or school. Consequently, each set of the four responses relating to the same aggressive behaviour act are combined into a single variable, so that each question now refers to having *'committed the behaviour at home, or in the neighbourhood or at the school or in another different place'*. Seven items are excluded from the study altogether – threatening to take the money of someone, threatening/forcing someone to move to another neighbourhood, stealing using a weapon, shooting someone with a weapon, committing homicide, attempting to rape, and committing rape. This was done due to very low frequencies of the acts (less than 25 cases for each of them), which would have produced unreliable results. Because of this exclusion and combining the place of the act, 14 items remained for this study. Table 1 gives the frequency distribution of the items. Some 72.4% of the adolescent sample has committed at least one of the aggressive behaviours in their lifetime; older children of course having had greater opportunity to do so.

Table 1 Adolescents scale items included in the survey on aggressive behaviour in adolescents from Medellin-Colombia (n=1686), 2007

Items (original questions is Spanish)	Never	Ever
Have you ever...		
Item 1: made fun of someone or making a practical joke?	835	849
Item 2: told hurtful words to someone?	1061	621
Item 3: humiliated or despised someone?	1323	359
Item 4: threatened someone?	1344	341
Item 5: threatened to hit someone with an object?	1544	142
Item 6: threatened to wound or kill someone?	1659	27
Item 7: stolen from someone without them noticing?	1541	142
Item 8: defraud or take advantage of someone?	1632	51
Item 9: hit another person with hands?	1164	517
Item 10: hit another person with an object?	1502	182
Item 11: thrown an object to someone?	1421	264
Item 12: attacked someone with a knife, pocket knife or bottle?	1656	25
Item 13: wounded someone?	1646	34
Item 14: touched somebody's buttocks, legs, breasts or genitals without agreement?	1650	34

Framework of measurement for aggressive behaviour

Item Response Theory

Item Response Theory is a set of quantitative procedures that have been developed to produce better psychological and educational outcome measures from self-reported surveys (Hays et al., 2000). These methods estimate the individual latent trait on a continuous scale, the so-called person parameters, and simultaneously the item parameters of severity and discrimination. Crucially these are all calibrated on the same measurement scale (Embretson and Reise, 2000). An important advantage of these methods is that they not only specify the probability of a person giving a positive response to the question according to its level of underlying latent trait, but also they provide a framework for evaluating the performance of the item both individually and as a set (Raudenbush et al., 2003). The Rasch model is the simplest of all item response models used to handle dichotomous response data for measuring latent variables (Bond and Fox, 2007). Importantly, it has a normative property, in that it defines which items are good measures of a trait and which items are poor measurements and should be rejected. Here, the nature of this specific IRT model is first considered before discussing these normative properties and how more complex models are specified and estimated.

The Rasch model

This model aims to estimate the probability of a person saying 'yes' to a particular item as a combination of just two terms: the difficulty, severity or rarity of the item on the one hand, and the person's individual propensity toward the behaviour, on the other (Johnson and Raudenbush, 2006, Doorenbos et al., 2005). This is illustrated graphically in Figure 3 that shows the *Item Characteristic Curve (ICC)* for three individuals (S1, S2 and S3) answering three items (Question 1, Question 2 and Question 3)of different severity under a Rasch model. The ICC describes the relationship between the probability of an affirmative response to an item on the vertical axis and the propensity or latent trait scale of aggressiveness on the horizontal.

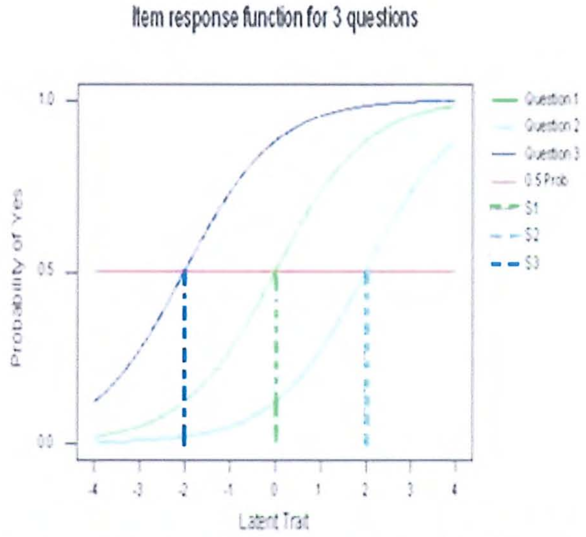


Figure 3 Three Item characteristic Curves for a Rasch Model

On the graph, item severity or item rarity is interpreted as the point on the horizontal-axis (propensity or latent trait) for which the probability of an affirmative response is 0.5. The greater the value, the greater the underlying propensity needed to have greater than a 0.5 chance of answering affirmatively. For instance, the adolescent (S3) with a low degree of aggressiveness (-2 compared to a mean of 0) has a 0.5 probability of saying 'Yes' to the least severe, more common Item –Question 3–, but a much lower probability of an affirmative response to more severe, less common items –Questions 2 and Question 3–. In contrast, subject (S2) with a higher degree of aggressiveness (+2) has a 0.5 probability of having committed the most severe and rarest occurring Item –Question 2–, and a higher probability of having committed the less severe items –Question 1 and Question 3–. Only the most seriously aggressive adolescent is likely to respond affirmatively to the most severe, that is the least common or rare behaviour.

More formally, the Rasch model, first developed by Georg Rasch (1901-1980) the Danish mathematician, statistician, and psychometrician, is usually specified as a non-linear model:

$$\pi_{ij} = \frac{e^{(u_j - \beta_i)}}{1 + e^{(u_j - \beta_i)}}$$

where the underlying probability π_{ij} of saying 'yes' to having committed an aggressive act for item *i* for person *j* is non-linearly related to u_j, the latent trait of aggressiveness for person *j* and to β_i which is the severity or difficulty of item *i*. The value *e* is the base of natural logarithms. This model is transformed to a linear one which is much easier for estimation and prevents impossible predictions outside the range of 0 and 1. This is done by taking a logit transformation (Kamata, 2001):

$$\log e\left(\frac{\pi_{ij}}{1 - \pi_{ij}}\right) = u_j - \beta_i$$

Consequently, the log odds of a person responding 'yes' to an item is the difference between the latent trait estimate and the item difficulty, and that is why it is known as a one-parameter model. For binary items, the model locates item difficulties and person propensities on the same log-odds (logit) scale, and it is these logits that are shown on the horizontal axis in Figure 3. This log-odds scale is an arbitrary but meaningful measurement scale which ranges from negative infinitive to positive infinity and includes a midpoint of zero, which is set at the mean of the persons and item estimates (Bond and Fox, 2007). In Figure 3 the vertical axis is the log-odds of an affirmative response, which has been transformed back to probabilities, and it can be clearly seen that only persons with high aggressiveness will have said 'yes' to having committed the most severe, rarest items of aggressive behaviour.

The Rasch model as a multilevel model

The Rasch model can be viewed as having a two-level structure with items nested within persons, so that it can be formulated as a member of the Hierarchical Generalized Linear Model (HGLM) family with random-effects (Kamata, 2001). In this case, the Rasch model will estimate the log-odds of an affirmative response at level 1, as a linear function of item indicators and have a random effect at level 2 which will give the person latent trait (Raudenbush et al., 2003).

In contrast to the fixed-effects approach that has been traditionally used to estimate Rasch models, where there is a separate regression coefficient for each and every person (as well as every item), the multilevel model applies a random-effects approach. Thus, the multilevel Rasch Model can be written as:

$$\pi_{ij} = \frac{e^{\beta_1 x_{1ij} + \beta_2 x_{2ij} \cdots + u_{0j}}}{1 + e^{\beta_1 x_{1ij} + \beta_2 x_{2ij} \cdots + u_{0j}}}$$

This non-linear model can be turned into a two-level linear model:

$$\log e\left(\frac{\pi_{ij}}{1 - \pi_{ij}}\right) = \beta_1 x_{1ij} + \beta_2 x_{2ij} + \ldots + u_{0j};$$

$$u_{0j} \sim N(0, \sigma^2_{u0}); \qquad Var(y_{ij} \mid \pi_{ij}) = \sigma^2_e \pi_{ij}(1 - \pi_{ij})$$

where β_1 is the coefficient, on the logit scale associated with the *i*th item dummy variable x_{ij} for person *j*, where *i* = 1, ..., *I*, that is, each item has been separately coded and there is no overall constant. This coefficient, when multiplied by -1, represents the item severity or item difficulty for item *i* on the logit scale. Similarly, β_2 is another fixed part averaged across all persons which represents, when multiplied by -1, the severity for item 2, again on the log-odds scale. There is such a fixed part term for each and every item. The term u_{0j} is the random effect or the individual latent trait, again on the logit scale for person *j*. A high value for individual j indicates a person with high aggressiveness; a low value is a person with a low propensity for this trait. The latent trait is conceived as coming for a Normal distribution with a common estimated variance, σ^2_{u0}. If this distributional assumption is not true, other latent variable methods need to be explored in order to establish the nature of the aggressive behaviour latent trait that best describes the data (see later). The level-1 unexplained variance between items assumes a Bernoulli distribution because of the binary nature of the response. That is, the observed outcome y_{ij} conditional on the estimated propensity π_{ij} has a variance that is determined by the predicted propensity and will reach a maximum when π_{ij} is 0.5 and a minimum when π_{ij} is either 0 or 1. Thus, the model has inbuilt heterogeneity as the variance will change with the mean. When the data are assumed to come from an exact Bernoulli distribution σ^2_e is constrained to 1, that is, it is not a parameter that is freely estimated (Snijders and Bosker, 1999). Thus, this specification of the Rasch model has the added advantage of modelling the measurement error in the observed items, which is represented by the lowest level within the hierarchical model (Raudenbush and Sampson, 1999a). In addition to handling errors of measurement, another particularly important advantage of this multilevel Rasch approach is that it is able to handle the missingness that occurs when not everybody has answered all questions. That is, when data are imbalanced with a potentially different number of items for each person. Moreover, unlike the standard fixed-effects model where dummies are included for each person, it can also handle invariant responses –such as respondents saying 'yes' or 'no' to all items.

This multilevel Rasch Model can be estimated using Monte-Carlo Markov Chain procedures which provides high quality estimates even where cluster size (the number of items per adolescent) is small (Browne, 2003). This method of estimation also provides the Deviance Information Criterion (DIC) for sequential model testing (Spiegelhalter et al., 2002). The DIC is a complexity-penalized badness-of-fit measure where lower values suggest a 'better' and more parsimonious model. Any reduction in the DIC is an improvement, but following experience with the more commonly applied AIC, differences greater than 4 suggest that the model with the higher DIC has considerably less support (Burnham and Anderson, 2002). Following Draper's advice on good-practice (Draper, 2008), initial starting values for the MCMC procedure are first obtained by quasi-likelihood estimates. Given the relatively small cluster size (number of items nested within an individual), these are likely to be under-estimates of the true values. Then, the MCMC procedure is run for a 'burn-in' of 500 simulations to get away from the quasi-likelihood values. These values are discarded. There is then a monitoring period of 50,000 further random draws. At the end of this monitoring period, the convergence of each model parameter is checked, which is shown by a lack of trend and nothing but 'white noise' variation. The existence of a trend would indicate that with a sample of 50,000 simulations the parameter has not reached its equilibrium position and that a longer burn-in is required. The information content of the model parameter estimates are also assessed, and further monitoring simulations are undertaken until the effective sample size of the Markov draws is equivalent to 500 independent draws. This procedure is time consuming involving, in complex modelling, days of estimation, but provides excellent characterisation of the degree of support, that is, empirical evidence for the value of parameter estimates.

Interpreting the Rasch Model: the item person map

Once a model is estimated, a particularly useful aid to the interpretation of the Rasch model is the Item-Person map, an example of which is shown schematically in Figure 4. As the Rasch model equates item difficulty and the latent trait on an arbitrary but common logit scale, items and traits can be directly compared on this 'map'. The 'map' displays the common horizontal latent trait on the logit scale. Above this scale is a histogram of the distribution of the estimated person-propensity (u_{0j}) for aggressive behaviour. Below the scale, the circles represent the items located according to their severity value (β_i). The map allows an appreciation that the Rasch model is giving both *norm* and *criteria* referencing for the adolescents. The Blue arrow indicates a person with very high aggressive behaviour who in terms of norms is in the top 3% of the sample, and in criterion terms has a greater than 50 percent chance of committing most of the items. In contrast, the Green arrow indicates someone with a low aggressiveness that in terms of norms is in the lowest 1% of the sample and in terms of criteria is likely to have committed only the two less severe acts of aggressive behaviour. Another aim of this map is to show how well the scale is adapted to the studied population, or whether this scale has insufficient 'rare' or 'severe' items, or insufficient 'less severe items' (Bond and Fox, 2007). This information allows evaluation of two of the desired properties of the aggressive behaviour items mentioned previously: the severity and the coverage. Examining the schematic results of Figure 4, adolescents on the right side have a higher propensity to respond affirmatively to the items on the lower left, which means that these are less severe items for persons with a high propensity. The few items located on the grey area may be more severe even for them, but they will say 'yes' to a much larger group of items located in the pink area. In contrast, the items on the lower right site are too severe for the persons on the upper left, which mean that those items are beyond their propensity level. In general, in this example, the items are lacking in information for adolescents who exhibit a high propensity for aggressive behaviour.

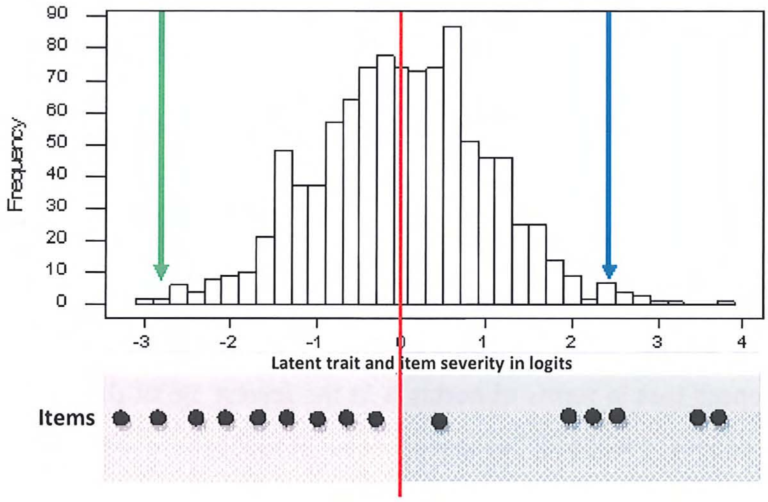


Figure 4 Person item map

Psychometric properties

The Rasch Model can also be used to provide a set of indicators and graphical displays to evaluate the correspondence of the data with the model. In general, these indicators assess the performance of each item and the overall function of the whole set of items for measuring the construct of interest in the population. Consequently, the reliability of item severity and then the information provided by the items can be evaluated.

Reliability of item severity

This index does not report on the quality of the data; however it specifies the replicability of the results in terms of the severity of the items, the difference between them and their placement on the severity pathway across other samples (Bond and Fox, 2007, Linacre and Wright, 2000). This index is represented by two calculations: the item separation index and the item reliability index.

The item separation index, determines the extent that item severities and difficulties are sufficiently spread out to define distinct levels of propensities measured in logits. It serves as an index of how well the set of items defines a pathway trait that includes both the low and the high end of the aggressiveness latent trait (Linacre and Wright, 2000). The index is expressed in standard error units as it is calculated as follows (based on Wright and Stone (1999), 165):

$$G = \frac{\sqrt{\left[\frac{\sum_{i=1}^{L}\beta_i^2}{L} - \left(\frac{\sum_{i=1}^{L}\beta_i^2}{L}\right)^2\right] - \frac{\sum_{i=1}^{L}\beta se_i^2}{L}}}{\sqrt{\frac{\sum_{i=1}^{L}\beta se_i^2}{L}}}$$

where L is the number of items, β_i is the severity for item *i* on the logit scale, β_{se_i} is the estimated standard error for item *i,* again on the logit scale. The estimate has a range from zero to infinity, where higher values than 2 are 'better' as they indicate that the items are adequately dispersed along the latent to define distinct levels of aggressive behaviour (Linacre and Wright, 2000, Piquero et al., 2002).

The item reliability index, on the other hand, is analogous to Cronbach's alpha (Wright and Stone, 1999). It estimates the replicability of the placement of the items along the hierarchy of severity across the adolescents with different levels of aggressive behaviour (Piquero et al., 2002). It is estimated as following:

$$R = G^2/(1 + G^2)$$

The estimated value ranges between 0 and 1, with values higher than 0.80 indicating that the results are stable and their location on the latent scale would be reliable over a repeated administration of the set of items in different samples. In contrast, low values mean that the sample is not big enough to precisely locate the items on the latent scale (Linacre and Wright, 2000).

Item Information Functions and the Standard error of Measurement

Another useful set of tools are concerned with information content, the quality and the precision or reliability of the measurement. Each item of the scale should produce some information about the latent trait of the person, and the Item Information Function (IIF) can be used to display how much information is provided for each item and for the scale as a whole and how well the item and the scale distinguish between individuals (Bond and Fox, 2007, Reeve and Fayers, 2005). An item provides the most information around its own severity level, which is the maximum information provided when the probability of an affirmative response is equal at 0.5. This is when the latent trait equals the item difficulty or severity. The IIF is estimated as a function of the model parameters, that is, as the product between the probability of saying 'yes' to having committed an aggressive act for item *i* for person *j* and the probability of not having committed an aggressive act for item *i* for person *j*, thus, it is:

$$IIF = \pi_{ij} * (1 - \pi_{ij})$$

Figure 5 shows the results for when there are just three items. The vertical axis represents the information magnitude and the horizontal axis the latent trait being measured by the scale. The most common or least severe item curve gives the peak information for persons with latent trait value of -2. When the trait is -4, the item gives less information, while this item gives almost no information for people with propensities higher than +2. The Moderate item curve gives most information for persons with a latent trait of zero, while the amount of information at -4 and +4 is negligible. Finally, the least common (less severe) item curve in the graph gives more information about persons with a higher propensity (more than +1), but little information about people with a lower propensity (less than zero).

Also shown in Figure 5 is the red line that represents the overall Test Information Function (TIF). This is simply the sum of the item information functions ($TIF = \sum_{i=1}^{n} IIF_i$) and indicates how well the whole scale matches the levels of the latent variable being studied. Ideally, the curve should be well spaced along the continuous latent trait (Reeve and Fayers, 2005). Here the combination of the three items gives more precise information for people between -2 and +2 on their latent trait, which suggests that the set of items give good overall information for persons from low to high propensities.

Inversely related to this information function is the *Standard error of measurement (SEM)*. It is estimated as $SEM = 1/\sqrt{TIF}$ and it is expressed in the same logit units as the item severity and the latent trait. Because information varies by latent trait, SEM evaluates how the precision of the scale varies across the different propensity levels (Reeve and Fayers, 2005). Figure 6 shows the SEM for the information functions shown in Figure 5. In this example, the scale is quite precise for people with propensity between -2 and 2, which is the range where there is more information available, while for persons outside this range the scale provides more imprecise scales with greater error. Both the Item Information Function and the Standard error of Information statistics allow assessment of two of the desirable properties for the aggressive behaviour scales highlighted above: coverage of the estimated scales and the validity of such measurements for different types of individuals.

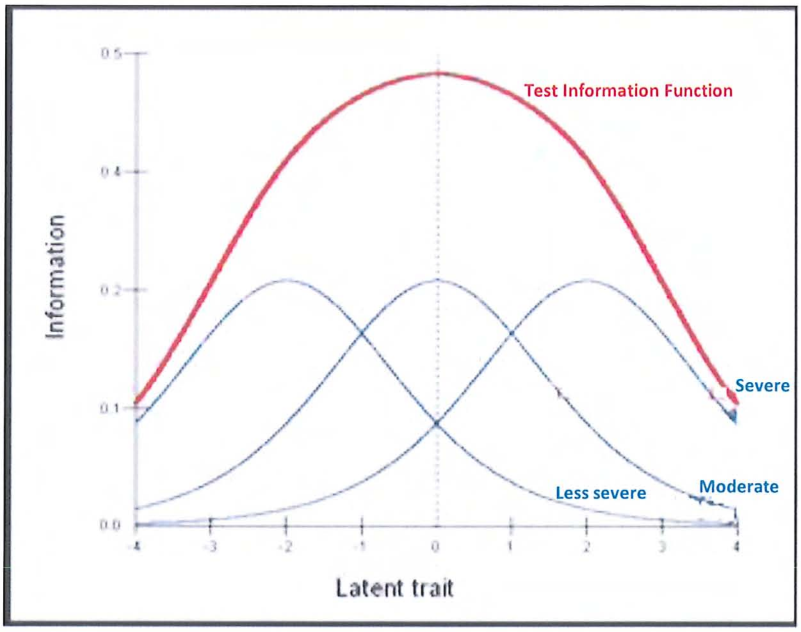


Figure 5 Item Information Function

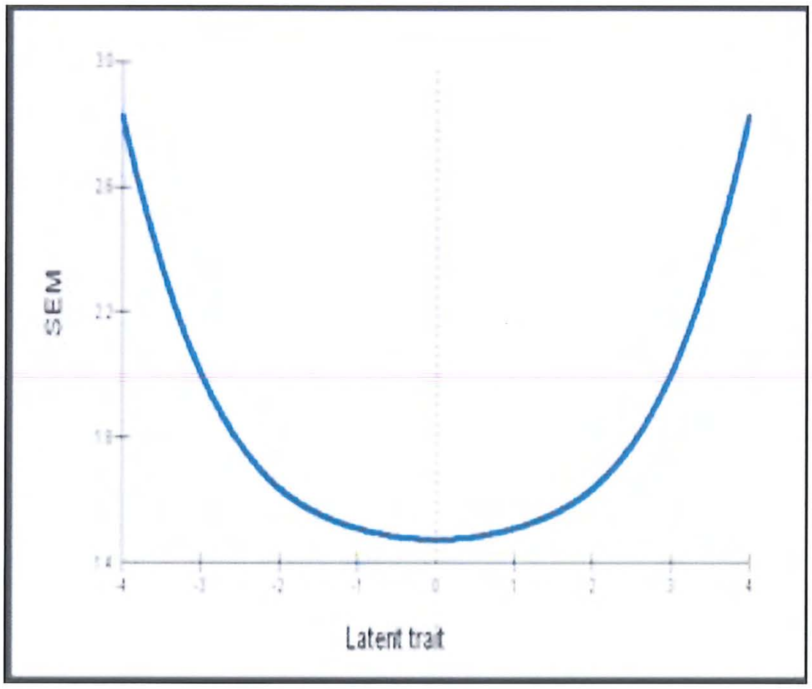


Figure 6 Standard Error of Measurement

Assumptions of the Rasch approach

Two assumptions – additivity and uni-dimensionality - have to be met for the Rasch model to be validly applied.

- *Additivity* refers to assumption that item severity and person propensity contribute additively to the log-odds (logit) of an affirmative item response. This requires that items are equally *discriminating*, that is, the rate at which the logit of an affirmative responses increases with the latent trait must be equal for all items (Bond and Fox, 2007). This assumption allows the interpretation of item difficulty as 'severity', so, that individuals with high scores on the scale display more severe levels of aggressiveness than do individuals with lower scores, and less frequently occurring behaviours are more severe (Raudenbush et al., 2003). Returning to Figure 3, discrimination is interpreted as the slope of the curve of the ICC at the 0.5 propensity. The Rasch model does not contain a parameter for item discrimination, it assumes, and indeed requires, that all items are equally discriminating and that the slopes of all the items are equal. This assumption is what defines the 'parallel curves' in the graph and for which this model is named as a one-parameter model within the family of the Item Response Theory models. Departures from this model assumption are shown in the ICC graph of Figure 7, in which the crossing of the item characteristic curves of each question reflects the different discriminating capacities of the items, and thus, the non-additive scales.

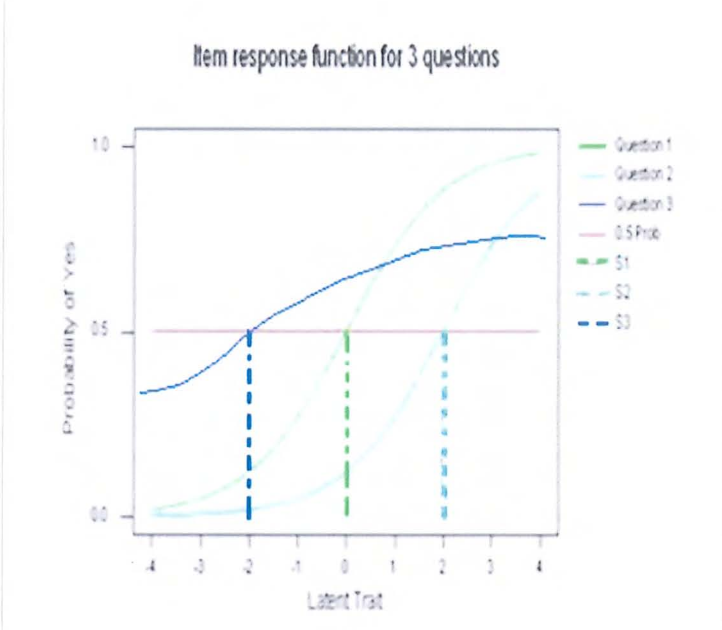


Figure 7 Non-additive Item Characteristic Curves: Two-parameter model

- *Uni-dimensionality* requires that the items essentially measure one and only one underlying dimension. This assumption allows differences in the frequency of affirmative responses to reflect differences in item severity or individual propensity rather than the presence of different dimensions.

When these assumptions are met, the resultant scale has several attractive advantages for the measurement of aggressive behaviour. First of all, the model yields item and person information that are easy to interpret. For example, item severity gives the scale a clear interpretation that items scoring high are more severe than are items scoring lower, and that this severity has identical meaning for all persons. Similarly, the model creates a meaningful continuous metric that appropriately reflects the varying seriousness of aggressive behaviour. This estimated latent trait allows unequivocal distinction between those who have high and low amounts of the latent trait. In a normative sense, good measurement is conceived as uni-dimensionality and additivity because, then and only then, can individuals be ranked unequivocally on the aggressive scale. Consequently, considerable attention needs to be given to validating both assumptions. This is achieved in two ways. First, staying with the Rasch model there are a variety of tools for assessing the quality of the model. Second more complex item response models can be fitted that allow for non-additivity and more than one dimension.

Tools for checking assumptions: item fit statistics

Once a Rasch model has been fitted, a number of statistics are available to aid in the diagnosis of any problems with the items and evaluation of the Rasch assumptions. Item fit statistic indices provide information about whether individual items fit the Rasch model, in particular the uni-dimensional assumption. This is done by indicating the degree of agreement between the pattern of observed responses and the modelled expectations. The main item fit diagnostics are the *outfit* and the *infit* mean square statistics (Bond and Fox, 2007). The outfit statistic is an un-weighted statistic sensitive to outlier responses. It indicates whether unusual responses are found based on person's propensities (e.g. a positive response to severe items given by individuals with low propensity of aggressive behaviour). In contrast, the infit statistic indicates the degree to which individual responses for a particular item meets the model expectations (Jackson et al., 2002). This indicator statistic gives relatively more weight to the performance of persons closer to the item severity value, and thus it is preferred to indicate quantitatively how appropriately each item fits the model, and to confirm the uni-dimensionality and construct validity of each item (Bond and Fox, 2007, Fisher Jr, 1993). This indicator is reported as a mean square statistic, which shows the degree of randomness in the response pattern and indicates the magnitude of the discrepancy between the observed response and the estimated latent trait. It is calculated as:

$$InfitMS_i = \frac{\sum_n z_{ni}^2 Var(\pi_{ij})}{\sum_n Var(\pi_{ij})} = \frac{\sum_n \left(\frac{y_{ij} - \pi_{ij}}{(Var(\pi_{ij}))^{1/2}}\right)^2 Var(\pi_{ij})}{\sum_n Var(\pi_{ij})} = \frac{\sum_n (y_{ij} - \pi_{ij})^2}{\sum_n Var(\pi_{ij})}$$

where y_{ij} is the observed response on item *i* by person *j*, π_{ij} is the estimated latent trait or score, $Var(\pi_{ij})$ is the model variance, also known as Information, which is estimated as described previously by $Var(\pi_{ij}) = \pi_{ij} * (1 - \pi_{ij})$. The value z_{ni}^2 is the standardized residual and it is estimated as $z_{ni} = \sqrt{\frac{y_{ij} - \pi_{ij}}{\pi_{ij} * (1 - \pi_{ij})}}$; n is the total sample size.

The infit mean squares statistics are expected to be equal 1. However, because Rasch is a probability model, acceptable fit statistics are generally accepted in the literature as ranging between 0.6 to 1.4 (Bond and Fox, 2007). Values between that range indicate that the scale is good enough in fitting a Rasch model and that that set of items contributes to the measurement of only one construct (the uni-dimensionality property mentioned earlier) (Duncan et al., 2003, Smith et al., 2008, López and Hidalgo, 2005). Items with values lower than 0.6 indicate less variation than expected by the model, which means that the response pattern is marginally closer to the expected pattern. In contrast, items with values higher that 1.4 suggest that the response pattern observed has more randomness than expected by the model.

The two-parameter item-response model

The procedures that have been discussed so far are based on statistics calculated from a Rasch model fitted to the available items. The Rasch model assumes that all the items are equally discriminating and, because of that, the severity of the items is identical for all persons. However, to evaluate whether the additivity assumption is met, a more sophisticated IRT model that includes an additional discrimination parameter for each item can be estimated. This model is known as a two-parameter model which includes a discrimination parameter for each item that allows the 'slopes' to vary across items. Lower values of this parameter are manifested as shallower slopes in the ICC graph and are associated with items that are less able to discriminate the latent trait of interest. Such a problematic ICC was shown previously in Figure 7. The crossing curves reflect items with more or less discriminating capacity. The steeper the curve, the better the item can discriminate and provide more information about a respondent. The flatter the curve indicates that the item has less ability to discriminate, since the probability of affirmative response at low propensity levels is relatively the same as it is at high propensity levels. In the two-parameter situation, and unlike the Rasch Model, item difficulty cannot be interpreted as severity since it depends on the level of propensity of the person.

The two-parameter IRT model is written as:

$$\log e\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \lambda_i(u_j - \beta_i)$$

where λ_i is the discrimination parameter or slope where the probability of a positive response is 0.5. In Figure 7, individuals with high propensities have a higher probability to give a positive response to Question 1 than Question 3, whereas individuals with lower propensities have a greater chance of answering positively to Question 3 than Question 2 or Question 1. The inclusion of item 3 is making it impossible to develop good-quality measurement of the underlying latent trait. Discarding this item should create a more coherent scale. This model can be estimated as a two-level multilevel logistic factor model in which the unknown latent trait (λ_j) is treated as a factor and the discrimination term (λ_j) as a loading on that factor. The model in this form can be estimated by using the GLAMM package (Zheng and Rabe-Hesketh, 2007).

The GLAMM model uses maximum likelihood estimation, which is equivalent to empirical Bayes estimation. As a confirmatory procedure, both the

Rasch and the two-parameter model are re-estimated as Full Bayesian models using the MCMC estimation approach available in the REALCOM package (Goldstein et al., 2008). Several computational advantages are found with this Full Bayesian approach. First of all, the Bayesian approach takes into account the uncertainty associated with all other parameters in the estimation of each specific parameter. In particular, it takes into account the uncertainty that the variance components are unknown when estimating the item parameters (Yang, 2006). Secondly, it estimates the variance components more accurately when there is a small sample size within a level; here there is a maximum of 14 items at the individual level (Yang, 2006). The Deviance Information Criteria can then be used to compare the two models where the model with the smaller DIC is chosen as the one that "best" fits the data (Spiegelhalter et al., 2002). For this analysis, a burn-in of 500 simulations is used, which are discarded, and a monitoring chain of 100,000 is used to obtain the final estimates.

It is important to stress that the aim of this two-parameter model as deployed here is not, as is usual in statistical modelling, to provide a better fit to the data, but the reverse. It is used to evaluate the additivity or equal discrimination assumption of the Rasch model, which is treated as the desired normative model of good measurement practice. In this sense, items with differential discrimination under the two-parameter model should be removed from the scale until the model can be best fitted by the one-parameter Rasch model. This procedure will guarantee that each scale will only include the set of items with the same discrimination power, which can be combined additively in order to determine more precisely the information about the underlying trait of aggressive behaviour.

Applying IRT models to measure aggressive behaviour

Having discussed the IRT models in some detail and recognizing their power over traditional approaches for estimating scales of aggressive behaviour, all these methods and associated procedures are now applied to the Medellin data.

Selecting items with Rasch properties

The process begins with an evaluation of the measurement properties of the 14 aggressive behaviour items. The aim is to select only those items that have the Rasch property of equal discrimination along the range of the underlying trait. In this step of the analysis, the strategy used by Raudenbush and Sampson when measuring the individual latent trait of criminal behaviour is followed (Raudenbush et al., 2003). Their strategy is an iterative process based on the comparison of the one-parameter Rasch model and the two-parameter model. This model comparison identifies items with differential discrimination under the two-parameter model which are then systematically removed from the model until the items better fit the one-parameter normative Rasch model. This model comparison can be undertaken by using methods for model selection of nested models: Likelihood ratio test, Bayesian information criterion or Deviance information criterion (Kang and Cohen, 2007). A non-significant chi-square value or smaller BIC/DIC estimates provide a statistical basis for accepting the simpler model, the one-parameter Rasch model in this case. This analysis is undertaken using the GLAMM package (Generalized Linear Latent and Mixed Models) in STATA version 9.0 (Stata Corp., College Station, USA).

The dataset structure used for fitting the one-parameter Rasch analysis and the two-parameter model in STATA is presented in Table 2. This shows the structure for 14 responses of two adolescents. Columns 1 and 2 relate to the adolescent ID and to the items to which they responded. Column 3 indicates the responses, where 1 indicates an affirmative answer and 0 indicates a negative answer. The values in the variable *wt2* are the person-level weights or number of adolescents with the same response pattern. The next 14 columns represent dummy variables associated with each of the 14 items. The use of the data in this form in which a binomial model is fitted rather than a Bernoulli binary outcome allows for more efficient estimation as the number of observations is substantially reduced without any loss of information (Subramanian et al., 2001).[1]

Table 2 Data structure for Rasch model specification using GLAMM framework

ID	variab	resp	wt2	item1	item2	item3	item4	item5	item6	item7	item8	item9	item10	item11	item12	item13	item14
1	1	0	463	1	0	0	0	0	0	0	0	0	0	0	0	0	0
1	2	0	463	0	1	0	0	0	0	0	0	0	0	0	0	0	0
1	3	0	463	0	0	1	0	0	0	0	0	0	0	0	0	0	0
1	4	0	463	0	0	0	1	0	0	0	0	0	0	0	0	0	0
1	5	0	463	0	0	0	0	1	0	0	0	0	0	0	0	0	0
1	6	0	463	0	0	0	0	0	1	0	0	0	0	0	0	0	0
1	7	0	463	0	0	0	0	0	0	1	0	0	0	0	0	0	0
1	8	0	463	0	0	0	0	0	0	0	1	0	0	0	0	0	0
1	9	0	463	0	0	0	0	0	0	0	0	1	0	0	0	0	0
1	10	0	463	0	0	0	0	0	0	0	0	0	1	0	0	0	0
1	11	0	463	0	0	0	0	0	0	0	0	0	0	1	0	0	0
1	12	0	463	0	0	0	0	0	0	0	0	0	0	0	1	0	0
1	13	0	463	0	0	0	0	0	0	0	0	0	0	0	0	1	0
1	14	0	463	0	0	0	0	0	0	0	0	0	0	0	0	0	1
2	1	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	2	0	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2	3	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0
2	4	0	2	0	0	0	1	0	0	0	0	0	0	0	0	0	0
2	5	0	2	0	0	0	0	1	0	0	0	0	0	0	0	0	0
2	6	0	2	0	0	0	0	0	1	0	0	0	0	0	0	0	0
2	7	0	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0
2	8	0	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0
2	9	0	2	0	0	0	0	0	0	0	0	1	0	0	0	0	0
2	10	0	2	0	0	0	0	0	0	0	0	0	1	0	0	0	0
2	11	0	2	0	0	0	0	0	0	0	0	0	0	1	0	0	0
2	12	1	2	0	0	0	0	0	0	0	0	0	0	0	1	0	0
2	13	0	2	0	0	0	0	0	0	0	0	0	0	0	0	1	0
2	14	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1

he analysis begins by comparing the estimates of the Rasch model and the two-parameter model. Table 3 shows the estimates and the standard errors for these two models. With the two-parameter model it is not possible to freely estimate all items and the variance simultaneously. Consequently, the estimates of the variance are given in two forms. The first set of estimates is when item 1 is arbitrarily chosen as the reference category and its discrimination is set at 1 and all other item discriminations are scaled to that parameter. The second set estimates all the item discriminations freely, but sets the variance of the trait to 1. This format is useful given that it provides the total discrimination value of each item, making it easy to evaluate the magnitude of their discriminatory power and allowing direct comparison between them. As described in the

[1] The only required modification to the Kamata (2001) specification of the model is that the level 1 variance is now $Var\ (y_{ij} \mid \pi_{ij}) = \sigma_e^2 \pi_{ij} (1 - \pi_{ij}) / n_{ij}$ where n_{ij} is the person-level weight or equivalently the number of adolescents with the same response pattern.

previous section, the two-parameter model allows a potentially different discrimination parameter for each item, taking into consideration the fact that some items may have stronger (or weaker) relations to the latent scale of aggressive behaviour than other items. This seems to be the case with the aggressive behaviour data. According to the estimates from Table 3, the items 5 (*'threatening to hit someone with an object'*), 6 (*'threatening to wound or kill someone'*), 10 (*'hitting another person with an object'*), 12 (*'attacking someone with a sharp object'*) and 13 (*'Wounding someone'*) are the most discriminating items, with values higher than 2. The least discriminating items are items 1 (*'making fun of someone'),* 2 (*'saying hurtful words to someone'*) and 3 (*'humiliating or despising someone'*), suggesting that these items may be exhibiting poor performance when measuring the aggressive behaviour scale or that they be measuring something else. In order to check which of the two models has a better fit to the data, the likelihood ratio chi-square test is used to compare nested models. The results are also displayed in Table 3 which gives the results of the one-parameter Rasch model and the two alternative forms of the two-parameter model. As can be seen, the chi-square test rejects the one-parameter model in favour of the two-parameter one ($p<0.001$) confirming that the two-parameter model fits the aggressive behaviour data significantly better, and that the items have different discriminations.

Table 3 Item parameters for the aggressive behaviour scale under the Rasch model and the two-parameter model

	Rasch model		Two-parameter				Two-parameter (fixed variance)	
Item	**Severity**	**se**	**Severity**	**se**	**Discrimina-tion**	**se**	**Discrimina-tion**	**se**
1. making fun of someone	0.02	0.07	0.03	0.06	1.00	(fixed)	1.26	0.10
2. saying hurtful words	-0.79	0.07	-0.70	0.07	1.00	-0.11	1.26	0.10
3. humiliate someone	-1.87	0.08	-1.71	0.09	1.06	-0.12	1.34	0.11
4. threatening someone	-1.97	0.09	-2.00	0.11	1.32	-0.15	1.67	0.13
5. threatening to hit someone with an object	-3.30	0.11	-3.97	0.26	1.80	-0.22	2.27	0.21
6. threatening to wound or kill someone	-5.32	0.21	-6.33	0.62	1.87	-0.33	2.36	0.38
7. stealing	-3.34	0.11	-3.27	0.18	1.24	-0.16	1.56	0.15
8.defrauding someone	-4.61	0.17	-4.50	0.29	1.24	-0.19	1.57	0.21
9. hitting someone with hands	-1.20	0.08	-1.19	0.09	1.26	-0.14	1.59	0.13
10. hitting another person with an object	-2.96	0.10	-3.83	0.26	2.00	-0.24	2.53	0.22
11. throwing an object to someone	-2.43	0.09	-2.48	0.14	1.35	-0.16	1.71	0.14
12. attacking someone with a sharp object	-5.45	0.23	-6.09	0.58	1.67	-0.31	2.11	0.35
13. wounding someone	-5.06	0.19	-6.81	0.85	2.26	-0.46	2.85	0.54
14.touching somebody's buttocks, legs, breasts or genitals without agreement	-5.09	0.20	-5.20	0.39	1.38	-0.24	1.74	0.27
Estimated variance	**2.64**	**0.16**	**1.59**	**0.25**			**1.00**	**0.00**
Log-likelihood		-7039	-7009					
Log-likelihood test ratio: One parameter model nested in two parameter model		LR chi2(13) = 59.94 Prob > chi2 = 0.0000						

This result is confirmed in Figure 8 of the estimated ICC's under the two-parameter model, using the values when item 1's discrimination is arbitrarily constrained to 1. The upper graph in the figure presents the probability of an affirmative answer on the vertical axis and the lower graph presents the analogous results on the logit scale. This facilitates the recognition of the items with crossing lines. The horizontal axis represents the propensity or latent trait on the logit scale. The plots show that the items do indeed cross. It is evident that adolescents with a high degree of aggressive behaviour are particularly likely to commit the most severe aggressive behaviour items, such as item 12 and 6, while adolescents with low aggressiveness are more likely to commit the other acts. This observation from the two-parameter model suggests that there is more than one dimension of aggressive behaviour in the set of items and that the 14 items have different discrimination power for different levels of aggressive behaviour. They are not measuring a one-dimensional scale of aggressive behaviour.

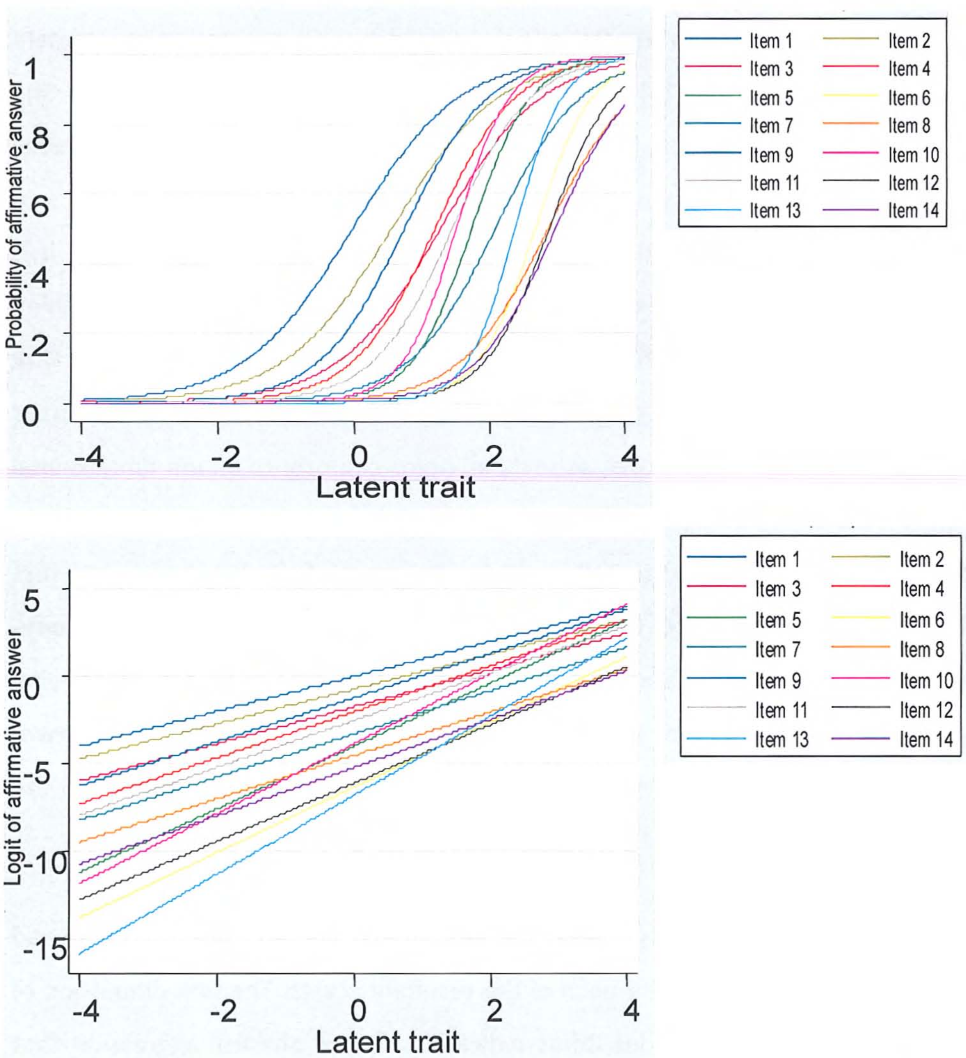


Figure 8 Item characteristic curves on the probability and logit scale for the aggressive behaviour items under the two-parameter model (with item 1's discrimination value constrained to 1)

When the models are estimated with Full Bayesian procedures in the REALcom software (Goldstein et al., 2008) comparable results are found. The DIC value for the Rasch model is 13296.8 and 13214.6 for the two-parameter model, indicating that there are items in the model that do not meet the Rasch property of equal discrimination.

At this stage of the analysis there are two ways to proceed. The first is split the items into groups on the basis of the item discriminations and repeat the analysis for all of them. The second is to discard one item at a time, starting with the item with the shallowest slope, until the Rasch model better fits the data. Both procedures are used and the same results are obtained. In the first procedure the items are split into two groups, where the first group is constituted by items with the steeper slope or higher discrimination parameters (items: 5, 6, 10, 12 and 13) and the second group is formed by the remaining items (items: 1, 2, 3, 4, 7, 8, 9, 11 and 14). The analysis of the first group of items again finds that the two-parameter model is the best fit to the data. The item with the lowest discrimination value at this stage is item 6. Consequently, it is excluded from the model and the analysis is re-run with the four remaining items. The result of the likelihood ratio test shows a value of 0.22, indicating that the set of four items is more parsimonious under the Rasch model than under the two-parameter model, and, as such, all items conform to an uni-dimensional scale (Table 5). Turning to the results of the analysis for the second group of items (which included additionally item 6), the result of the likelihood ratio test show a large p-value (0.24) indicating that the 10 items are best fitted by a one-parameter Rasch model and thus, that all the items have the same underlying slope. Results from the alternative method of analysis also found two-dimensions of aggressive behaviour, with a group formed by four items and the other by the remaining 10 (Table 4).

Table 5 and Table 4 show the item parameters under the Rash model and the two-parameter model for each of the resultant scales. The first dimension of aggressive behaviour includes items indicating acts of physical aggression that purposely damage others, such as threatening with or using a weapon. Item 10 *'hitting someone with an object'*and item 5 *'threatening to hit someone with an object'* are the less severe items within this dimension of aggressive behaviour. Item 12 *'attacking someone with a sharp object'*, and item 13 *'wounding someone'* are the most rare or more severe acts (Table 4).

Table 4 Item parameters for the first dimension of aggressive behaviour under the Rasch model and the two-parameter model

	Rasch model		Two-parameter				Two-parameter (fixed variance)	
Item	**Severity**	**se**	**Severity**	**se**	**Discrimination**	**se**	**Discrimination**	**se**
5. threatening to hit someone with an object	-4.79	0.29	-4.50	0.57	1.00	(fixed)	2.71	0.45
10. hitting another person with an object	-4.31	0.27	-4.80	0.85	1.25	0.43	3.39	0.7
12. attacking someone with a sharp object	-7.61	0.43	-6.99	0.9	0.97	0.24	2.63	0.52
13. wounding someone	-7.16	0.41	-6.69	0.88	1.00	0.25	2.71	0.54
Estimated variance	**8.91**	**1.33**	**7.37**	**2.45**			**1.00**	**0.00**
Log-likelihood		-1168.27	-1166.04					
Log-likelihood test ratio: One parameter model nested in two parameter model		LRchi2(3) = 4.46 Prob > chi2 = 0.22						

The correspondent ICC graph under the Rasch Model also shows this information. The Item 10 *'hitting someone with an object'* is the least severe item and item 12 *'attacking someone with a sharp object'* is the most severe (Figure 9).

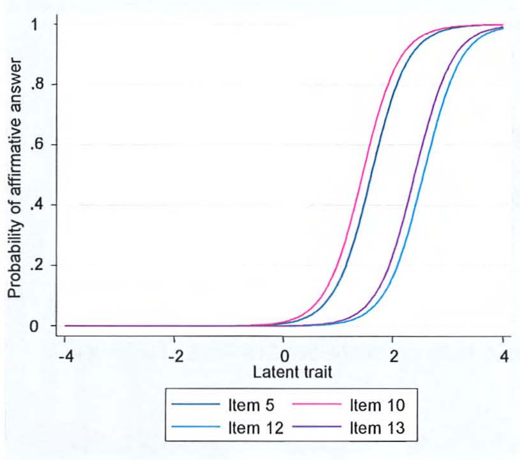


Figure 9 Item characteristic curves on the probability scale for the first dimension of aggressive behaviour under the Rasch model

The second dimension consists of 10 items that include acts of physical aggression, together with other forms of antisocial behaviour such as verbally offending or degrading others, theft and sexual abuse. Within this aggressive behaviour scale, items 1 and 2, '*making fun of someone*' and '*saying hurtful words to someone*' are the less severe or most common behaviour among the adolescents. Items 6 '*threatening to wound or kill someone*' and 14 '*touching somebody's buttocks, legs, breasts or genitals without agreement*' are the most severe items (Table 5).

Table 5 Item parameters for the second dimension of aggressive behaviour under the Rasch model and the two-parameter model

	Rasch model		Two-parameter				Two-parameter (fixed variance)	
Item	Severity	se	Severity	se	Discrimination	se	Discrimination	se
1. making fun of someone	0.02	0.07	0.02	0.07	1.00	(fixed)	1.41	0.11
2. saying hurtful words	-0.77	0.07	-0.72	0.07	0.94	0.11	1.32	0.11
3. humiliate someone	-1.83	0.08	-1.73	0.1	0.96	0.11	1.35	0.12
4. threatening someone	-1.93	0.08	-2.11	0.13	1.3	0.16	1.83	0.16
6. threatening to wound or kill someone	-5.20	0.21	-5.66	0.51	1.32	0.26	1.87	0.32
7. stealing	-3.22	0.11	-3.43	0.2	1.24	0.16	1.75	0.17
8.defrauding someone	-4.49	0.16	-4.7	0.34	1.22	0.20	1.71	0.24
9. hitting someone with hands	-1.16	0.08	-1.27	0.1	1.28	0.16	1.81	0.16
11. throwing an object to someone	-2.34	0.09	-2.2	0.11	0.94	0.12	1.33	0.12
14.touching somebody's buttocks, legs, breasts or genitals without agreement	-4.95	0.19	-5.03	0.38	1.13	0.21	1.60	0.26
Estimated variance	**2.40**	**0.16**	**1.99**	**0.32**			**1.00**	**0.00**
Log-likelihood		-6105.52	-6099.71					
Log-likelihood test ratio:		LR chi2(9) = 11.61						
One parameter model nested in two parameter model		Prob > chi2 = 0.24						

This ranking of the items is more clearly represented in the item characteristic curves (ICC) displayed in Figure 10. The graph shows that, an adolescent with a middle propensity of a zero logit is highly likely to respond affirmatively to the less severe items (such as item 1 *'making fun of someone'*) and more unlikely to response affirmatively to the more severe item (item 6 *'threatening to wound or kill someone'*). Only adolescents with higher propensities of aggressive behaviour (+2) are likely to respond affirmatively to the latter items.

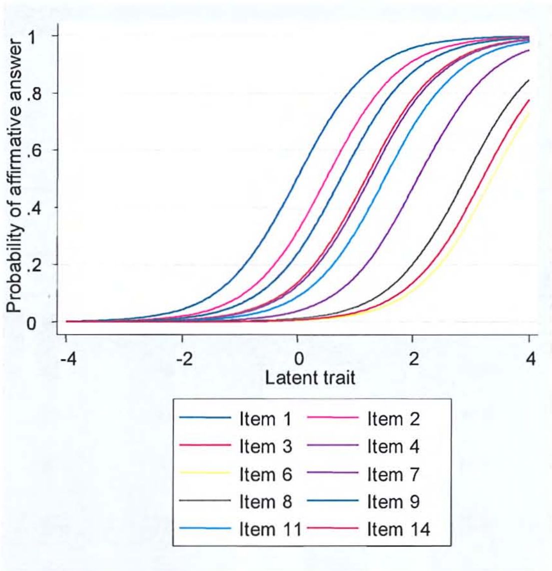


Figure 10 Item characteristic curves on the probability scale for the second dimension of aggressive behaviour under the Rasch model

The analysis has so far revealed that there are two scales, with both of them having Rasch-like properties. The results of this item-selection process have considerable face validity, and make good intuitive sense about two different types of aggressive behaviour that can be named from now on as *delinquency* and *aggression*.

Item fit and interpretation

Having clearly identified two separate scales with the Rasch properties, it is now possible to evaluate the performance of the items within each scale and estimate the corresponding latent traits for each adolescent. The Rasch model is estimated as a two-level model, with items nested within persons, by using MCMC estimation procedures (Browne, 2003) in MLwiN 2.22 (Rasbash et al., 2008). The length of the monitoring chain used is 50,000, following an initial maximum likelihood estimation and a burn-in period where 500 simulations are discarded. The simulation is stopped when the monitoring chain of each and every parameter have an effective sample size higher than 500.

The purpose of using this software is that its storage of estimates and its macro language allows the calculation of a variety of post-estimation statistics to evaluate the psychometric properties and the diagnostics. Appendix 2 gives a set of macros that were written by the present researcher to calculate and display the corresponding item maps, test information function, standard error of measurement and item *infit* statistics. The Winsteps software provided by (Bond and Fox (2007) is also used to fit the Rasch model and obtain item reliability measures.

Table 6 displays the variables and structure of the data for this analysis for the delinquency scale. The first four columns are dummy variables for the four items. The fifth variable 'Resp' is the 'long' item response binary vector containing the four item responses for each adolescent. Examining this response vector, the data for each adolescent consist of four rows and then the adolescent ID (Person's column) is repeated four times. As a result, the whole data set contains 4 x 1686 = 6,744 rows. The seventh column indicates the number of the item which is related to the response, and, the last column is a constant, which is a vector of ones. This structure of the data is the same for the aggression scale.

Table 6 Data structure for multilevel Rasch model using the MLwiN framework

	Items_1(6744)	Items_2(6744)	Items_3(6744)	Items_4(6744)	Resp(6744)	Persons(6744)	Items(6744)	Const(6744)
1	1.000	0.000	0.000	0.000	0.000	1.000	1.000	1.000
2	0.000	1.000	0.000	0.000	0.000	1.000	2.000	1.000
3	0.000	0.000	1.000	0.000	0.000	1.000	3.000	1.000
4	0.000	0.000	0.000	1.000	0.000	1.000	4.000	1.000
5	1.000	0.000	0.000	0.000	0.000	2.000	1.000	1.000
6	0.000	1.000	0.000	0.000	1.000	2.000	2.000	1.000
7	0.000	0.000	1.000	0.000	0.000	2.000	3.000	1.000
8	0.000	0.000	0.000	1.000	0.000	2.000	4.000	1.000
9	1.000	0.000	0.000	0.000	0.000	3.000	1.000	1.000
10	0.000	1.000	0.000	0.000	0.000	3.000	2.000	1.000
11	0.000	0.000	1.000	0.000	0.000	3.000	3.000	1.000
12	0.000	0.000	0.000	1.000	0.000	3.000	4.000	1.000
13	1.000	0.000	0.000	0.000	0.000	4.000	1.000	1.000
14	0.000	1.000	0.000	0.000	0.000	4.000	2.000	1.000
15	0.000	0.000	1.000	0.000	0.000	4.000	3.000	1.000
16	0.000	0.000	0.000	1.000	0.000	4.000	4.000	1.000

Interpreting the results from the two-level model

The results of the higher-level random part for aggression and delinquency scales are shown in Table 7. The results show significant variation between adolescents in both the aggression and delinquency scales ($p < 0.001$). The variance between adolescents on the delinquency scale is particularly large at 8.93.

Table 7 Random component estimates from the multilevel multivariate model for the aggressive behaviour scales

Random Part	Variance	Std. Err.	95% Percent Credible Interval
Adolescent			
Aggression	2.41	0.16	(2.12 - 2.74)
Delinquency	8.93	1.34	(6.72 - 11.96)

The variance parameters are the medians of 100,000 and 50,000 chains, with a burn-in of 500. The limits of the 95 percent credible intervals are 2.5% and 97.5% points of the distribution of the chains.

Item fit of the aggression scale

The estimates of the item severities and the estimated individual latent traits adjusted for measurement error are displayed on the item-person map (Figure 11). The horizontal axis represents the underlying propensity or latent trait on the logit scale. The vertical bar represents the distribution of the adolescents-propensities and the circles represent the items according to their severity position on the logit scale. According to the graph, the adolescent propensity ranges from -1.53 to 4.85 logits, with 50% of the adolescents presenting aggression levels lower than the mean logit (zero on the logit scale). The Item-person map also suggests a coherent ordering of the items. As reported earlier, item 1 (*'making fun of someone'*) and item 2 (*'saying hurtful words to someone'*) are the less severe items (with a logit under 1) and almost 30% of the adolescents sample exhibit levels of aggression sufficient to commit those acts. It can also be seen in the graph that most severe items such as item 6 (*'threatening to wound or kill someone'*) and item 14 (*'touching somebody's buttocks, legs, breasts or genitals without agreement'*) are placed on the right side of the graph. Very few adolescents (less than 1%) have propensity levels to say 'yes' to that set of items. However, although few, they are the most likely to have responded affirmatively to both the most severe items and all the less severe items. The results from the separation index statistic show a value of 15.9 and the reliability of the item severity is high (1.00), suggesting that the items create a scale that is well defined and that the item spread along the scale is good.

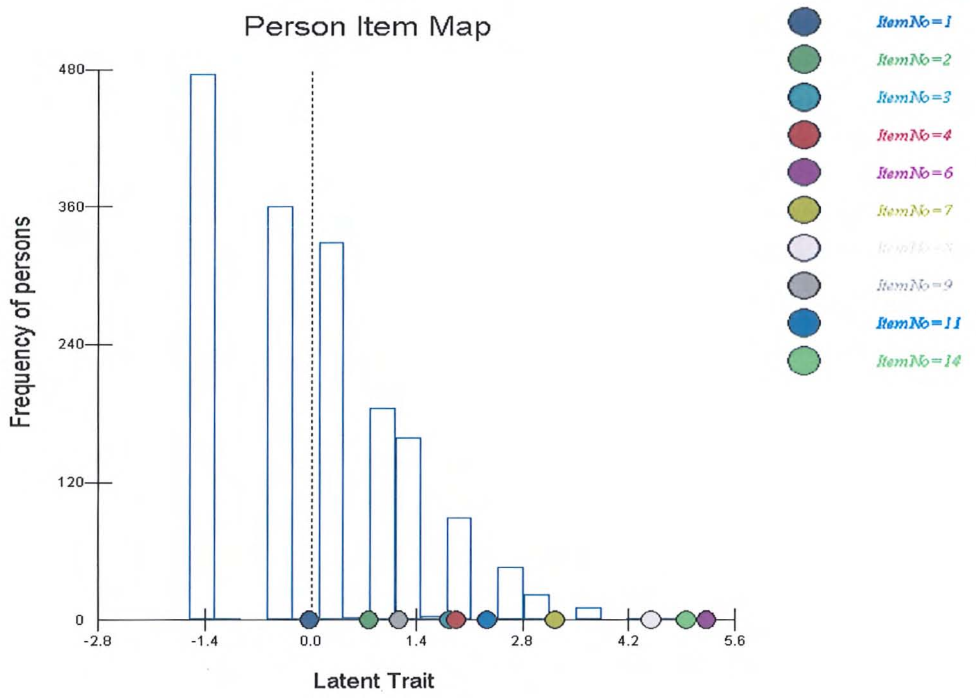


Figure 11 Item- Person map for the aggression scale

The item information function, test information function and the associated reliability of the newly created scale are displayed in Figure 12. In these graphs the items are numbered on a sequence from 1 to 10 following the order of the previous graphs. It is evident that the set of aggression items covers a wide range of the aggression propensity and that it is more reliable for measuring aggression higher than the mean logit. This result is confirmed with the graph of the standard error of measurement. Comparing the TIF curve with the distribution of the estimated latent trait of aggression of the adolescents, it can be said that the set of items measuring aggression is able to discriminate precisely and with high reliability among the adolescents in the middle and high part of the latent trait range.

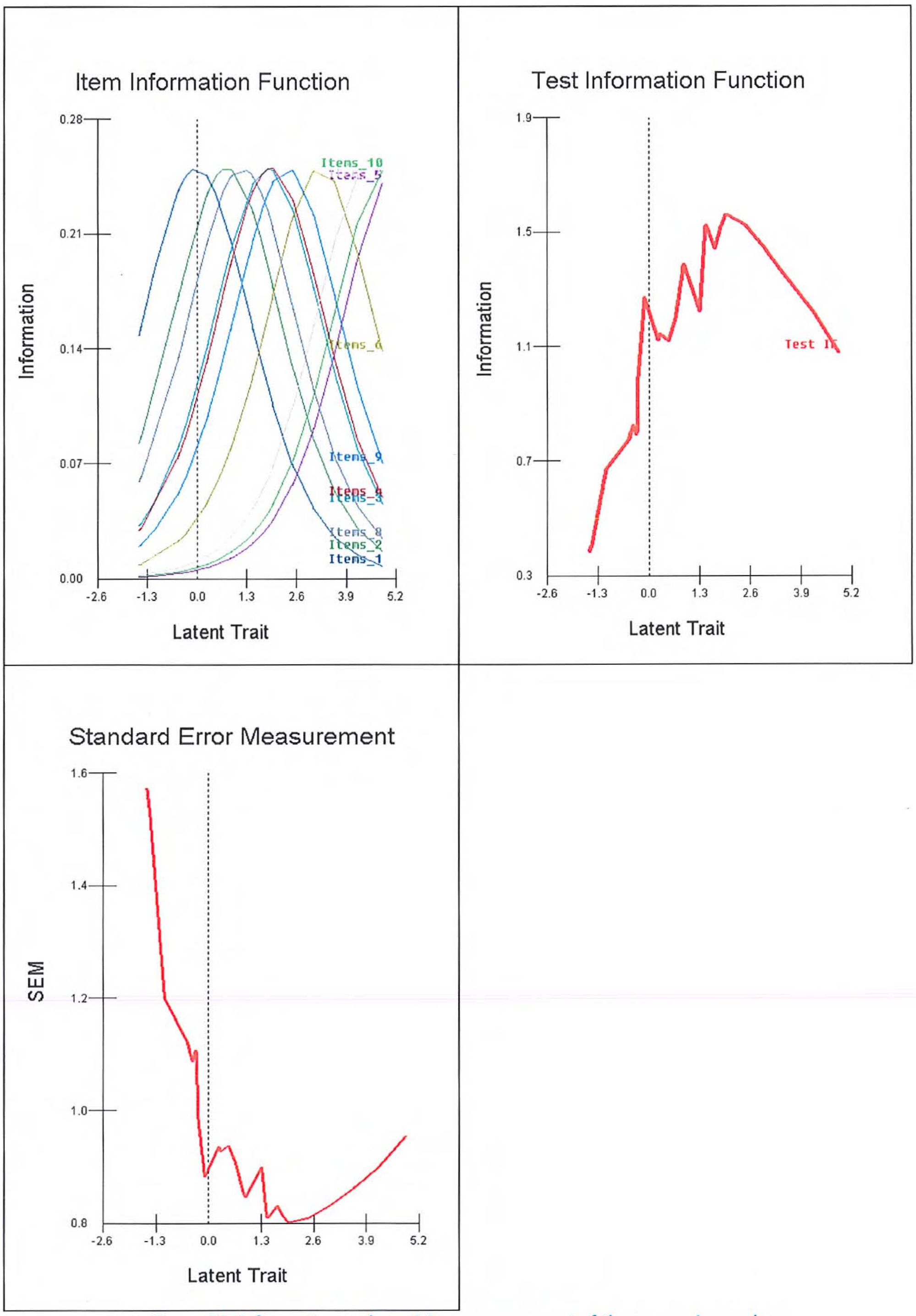


Figure 12. Information and precision measurement of the aggression scale

Finally, the Rasch *infit* statistics are shown in Figure 13 as an *item pathway diagram.* This graph shows the placement of the items in terms of their severity and their *infit* value (in their Mean Square form). In the figure, the item severity is represented by the location of the triangles. The triangles at the bottom of the path symbolize the less severe items, and those at the top are the more severe. The ordering of the items in this graph matches with the order showed in the item person map discussed earlier. A visual examination of the figures reveals that the fit of the items to the Rasch model is good (they are well within the 'tramlines' of acceptable misfit of 0.6 and 1.4), and thus the ten items can be combined effectively to produce a meaningful measure of individual aggression.

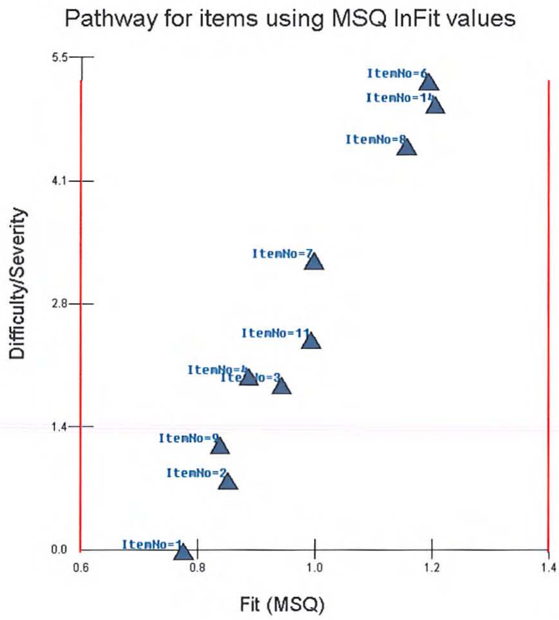


Figure 13 Item pathway of the aggression scale

Item fit of the delinquency scale

Figure 14 shows the item person-map for the delinquency scale. It is immediately apparent that the set of items is more severe than the majority of the adolescents. The range of the latent scores of the adolescents is between -0.79 and 8.06, being 85% of the adolescents having delinquency levels lower than the mean logit (0 logit). Items 13 and 12 are on the extreme end of the scale, with parameters estimated to exceed the mean logit, suggesting that only adolescents with high levels of delinquency (≥8 logits) will endorse these items (0.53% of the adolescents). The separation index statistic is estimated at 8.9, indicating good separation in terms of severity among the items. The reliability of the item severity showed a coefficient of 0.99, which suggests that the hierarchy of the items along the pathway is very precise and that replicability of item severity can be expected across other samples.

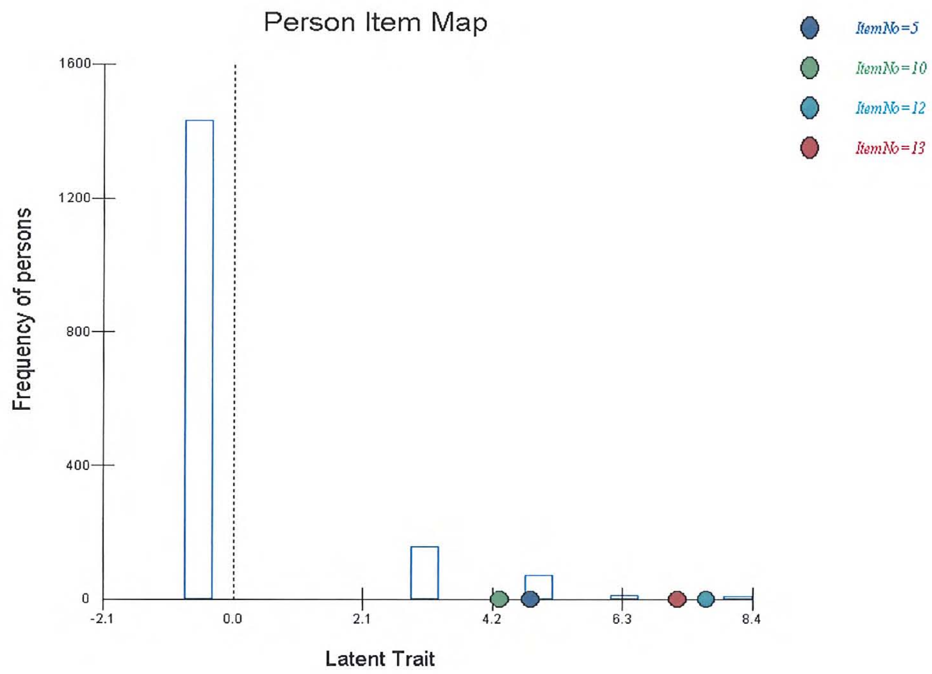


Figure 14. Item- Person map for the delinquency scale

Evaluation of the item and test information function (

Figure 15) shows that the set of delinquency items is most powerful at distinguishing among individuals with latent trait values higher than the average (around +4.0 logits). The scale is less reliable or imprecise for measuring delinquency at the lower end of the scale. This observation is confirmed by the plot of the standard error of measurement, which shows that only levels of delinquency above a logit of +3 are measured precisely. Comparing the distribution of the adolescents latent trait of delinquency with the standard error of measurement curve, it can be observed that 85% of the adolescents have latent trait values under +2 logits, exactly where the scale is most imprecise to discriminate among people.

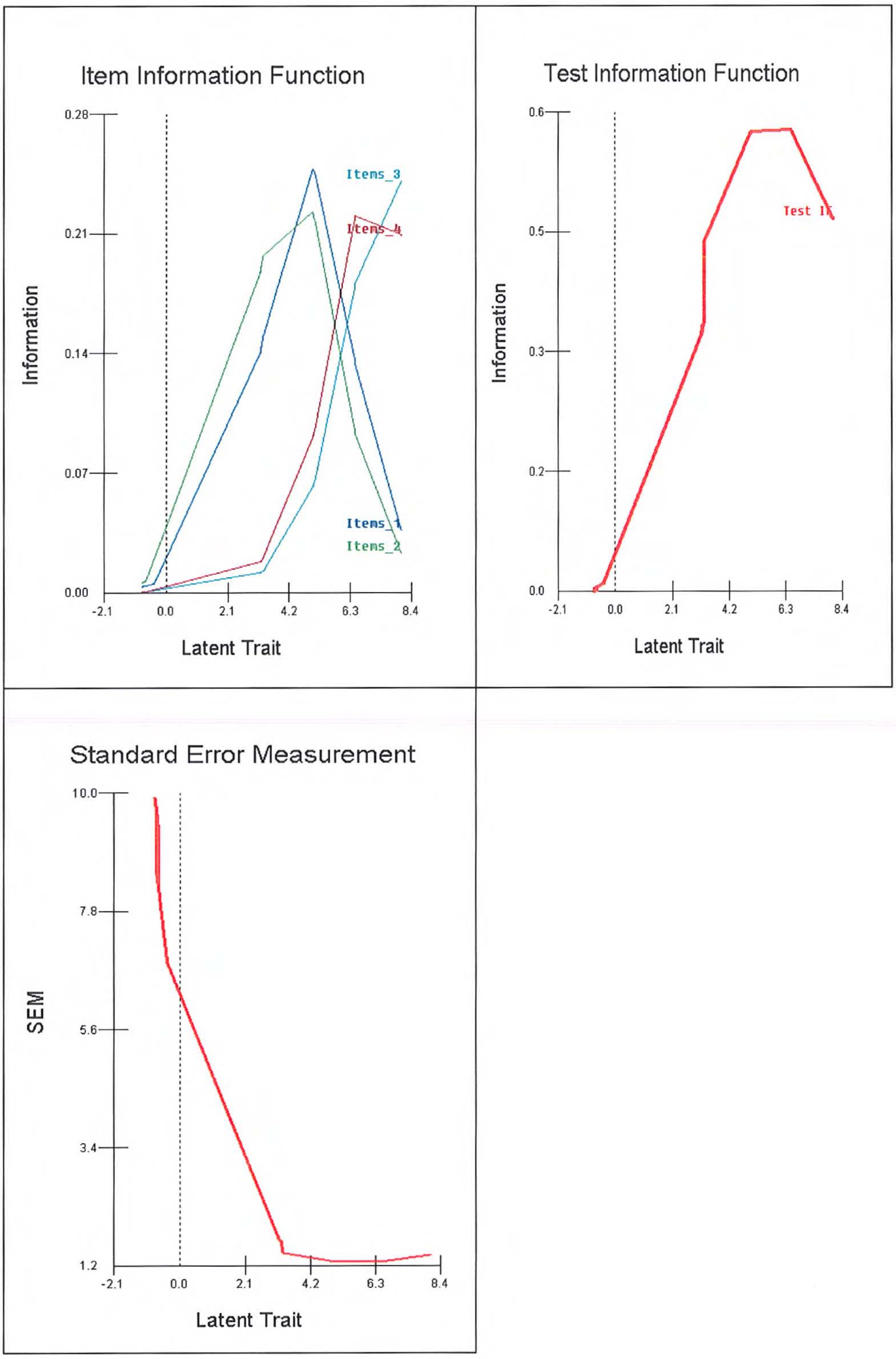


Figure 15 Information and precision measurement of the delinquency scale

Finally, the analysis turns to the item fit statistics for delinquency (Figure 16). The mean square values show that all the items meet the evaluation criteria, with values inside the expected range. This result confirms that the items fit well to the Rasch model.

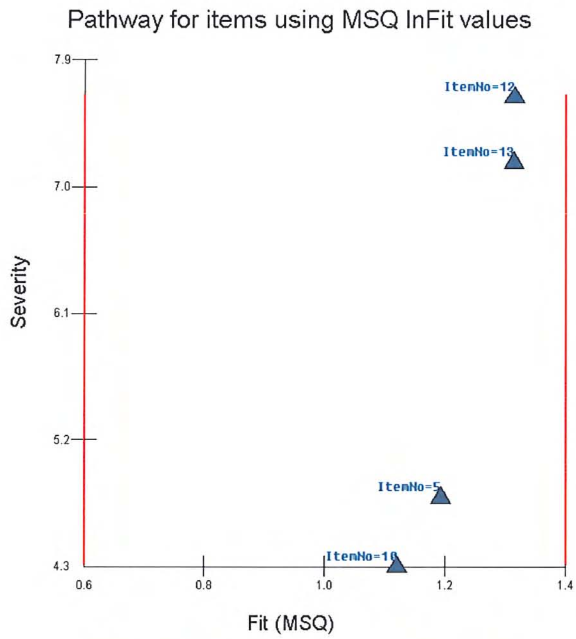


Figure 16 Item pathway of the delinquency scale

The Rasch model as a multilevel multivariate model

So far, the aggression and delinquency scores have been estimated separately; however, it is possible to assess the extent to which these types of aggressive behaviour are correlated. This is achieved by extending the multilevel Rasch model to a multivariate model in which the two dimensions of aggressive behaviour dimensions are analyzed jointly and their covariance (and when standardised their correlation) is estimated (Raudenbush et al., 2003). In this model the log-odds, for the aggressive behaviour dimensions for adolescent *j* is specified as:

$$y_{ij} \sim Binomial\ (Denom_{ij}, \pi_{ij})$$

$$\log e\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = D_{AGij}(\beta_{0AG} + \beta_1 x_{1ij} + \beta_2 x_{2ij} + \ldots + \beta_{i-1} x_{i-1j} + u_{AG0j} x_{0ij}) +$$
$$D_{DEij}(\beta_{0DE} + \beta_1 z_{1ij} + \beta_2 z_{2ij} + \ldots + \beta_{i-1} z_{i-1j} + u_{DE1j} x_{0ij})$$

$$u_{AG1j} \sim N(0, \Omega_u) \qquad \Omega_u = \begin{bmatrix} \sigma^2_{u1} & \\ \sigma_{u12} & \sigma^2_{u2} \end{bmatrix}$$
$$u_{DE1j} \sim N(0, \Omega_u)$$

$$Var(y_{ij} \mid \pi_{ij}) = \sigma^2_e \pi_{ij}(1-\pi_{ij})$$

where, y_{ij} is again the set of binary responses for item *i* as reported by adolescent *j*. Denom is a set of 1's. The estimated probability of saying 'yes' to item *i* for person *j* is given by π_{ij}. The two terms, $D_{AG\,ij}$ and $D_{DE\,ij}$, are indicator variables, where $D_{AG\,ij}$ takes the value of 1 if the *ith* response is an item measuring aggression and a value of 0 otherwise. In the same way $D_{DE\,ij}$ takes the value of 1 if the *ith* response is an item measuring delinquency and a value of 0 otherwise. The specific aggression and delinquency items are represented by x_{ij} and z_{ij} respectively. This specification differs from the one given by Kamata (2001) and follows Cheong and Raudenbush (2000), in that each dummy is centred around its mean (1/*n*, where *n* representing the number of items of each scale of aggressive behaviour). As shown in Table 8, there are 4 items for the delinquency scale, so the dummies are replaced by (dummy - 1/4), that is (dummy - 0.25) and, as there are 10 items for the aggression scale, the dummies are (dummy - 0.10). The importance of this specification is that, β_{0AG} can then be interpreted as the log-odds of a *typical* adolescent (defined in terms of their latent trait) responding affirmatively to a typical aggression item. Equivalently,

β_{0DE} is interpreted as the log-odds of a *typical* adolescent responding affirmatively to a typical delinquency item. The adolescent random effects for the aggression scale are given by $u_{AG0j}x_{0ij}$, while for the delinquency by $u_{DE1j}x_{0ij}$. These random effects are assumed to be Normally distributed with zero means, and variances given by σ^2_{u1} representing the adolescent-level variance for the aggression scale, and, σ^2_{u2} representing the variance for the delinquency scale. The covariance term σ_{u12}, when divided by the product of the square root of the variances:

$$corr\ (u_{1j}, u_{2j}) = \sigma_{u12} / (\sigma_{u1} + \sigma_{u2})$$

gives the correlation between the two scales. Finally, $\sigma^2_e \pi_{ijk}(1 - \pi_{ijk})$ represents the level 1 variance that is associated with the Bernoulli weight, which is constrained to 1.

Table 8 Data structure for multilevel Rasch model using Cheong and Raudenbush formulation

	Items(6744)	Resp(6744)	NhoodL(6744)	Persons(6744)	Const(6744)	Item1(6744)	Item2(6744)	Item3(6744)	Item4(6744)
1	1.000	0.000	103.000	1.000	1.000	0.750	-0.250	-0.250	-0.250
2	2.000	0.000	103.000	1.000	1.000	-0.250	0.750	-0.250	-0.250
3	3.000	0.000	103.000	1.000	1.000	-0.250	-0.250	0.750	-0.250
4	4.000	0.000	103.000	1.000	1.000	-0.250	-0.250	-0.250	0.750
5	1.000	0.000	103.000	2.000	1.000	0.750	-0.250	-0.250	-0.250
6	2.000	1.000	103.000	2.000	1.000	-0.250	0.750	-0.250	-0.250
7	3.000	0.000	103.000	2.000	1.000	-0.250	-0.250	0.750	-0.250
8	4.000	0.000	103.000	2.000	1.000	-0.250	-0.250	-0.250	0.750
9	1.000	0.000	103.000	3.000	1.000	0.750	-0.250	-0.250	-0.250
10	2.000	0.000	103.000	3.000	1.000	-0.250	0.750	-0.250	-0.250
11	3.000	0.000	103.000	3.000	1.000	-0.250	-0.250	0.750	-0.250
12	4.000	0.000	103.000	3.000	1.000	-0.250	-0.250	-0.250	0.750

The results of this model estimated by MCMC procedures using MLwiN v2.22 are shown in Table 9. For this model a burn-in of 500 iterations is used, with monitoring for a further 50,000 iterations. The results showed that the expected logit of answering affirmatively an aggression item for a typical adolescent is -2.59 and the corresponding median probability is 7.0% (95% CI 6.2% ; 7.7%). The logit of endorsement of a delinquency item for a typical adolescent is -5.97, the corresponding median probability is 0.3% (95% CI 0.1% ; 0.5%), much less than for aggression. The estimates of the higher-level random part for aggression and delinquency scales are shown in Table 9. The estimates of the item severities are not shown as they are essentially unchanged compared to those of the previous two-level model. For the random terms, the values of between adolescents variance are, as would be expected, quite close to those showed in Table 7, when they are estimated separately. The new parameter estimated in this model is the covariance parameter which is highly significant ($p<0.01$). The estimated covariance between adolescents is 3.84. The estimated correlation of the two aggressive behaviour scales at the individual level is consequently 0.83. Thus, there is a tendency for both latent traits of aggressive behaviour to be strongly correlated; individuals have a tendency for both aggression and delinquency while the former is much more prevalent in the Medellin population.

Table 9 Covariance component estimates from the multilevel multivariate model for the aggressive behaviour scales

Random Part	Variance	Std. Err.	95% Credible Interval
Adolescent			
Aggression	2.39	0.16	(2.11 - 2.72)
Delinquency	8.93	1.27	(6.62 - 11.66)
Covariance	3.84	0.33	(3.23 - 4.54)

The variance parameters are the medians of 50,000 chains, with a burn-in of 500. The limits of the 95 percent credible intervals are 2.5% and 97.5% points of the distribution of the chains.

Conclusions

At the outset of this chapter, six desirable psychometric properties for measuring aggressive behaviour as an underlying latent constructs are highlighted. By using a wide range of statistical approaches, a coherent approach has been developed to derive uni-dimensional reliable valid scales which distinguish the more severe acts of aggressive behaviour from others. Procedures have been used that adjust for measurement error and assess the coverage of the range of behaviour measured by the resultant scales. A key aspect of this is the emphasis on the Rasch property of measurement, whereby only items that are equally discriminating are included in a scale. At the outset of a two parameter IRT model specified as a multilevel model, is used to simultaneously estimate the severity and discrimination of the items and the underlying trait. This is seen as a screening procedure to find a uni-dimensional scale which can then be appropriately analysed by a one-parameter Rasch model. This procedure is then used to report the severity of items and to characterise the reliability and the nature of the scales. A multivariate extension of this model allows comparison between more than one scale in an overall model.

The two-parameter multilevel analysis revealed that there are two different aggressive behaviours for Medellin adolescents: one consisting of ten items measuring aggression and the second consisting of four items measuring delinquency. The separate estimation of each set of items through the multilevel Rasch placed the item measurements on a continuous scale. Evidence of construct validity is provided by the item analysis which reveals a theoretically sensible ordering of severity, where the items *'attacking someone with a sharp object'* and *'stealing with gun'* are the most severe items for the delinquency scale. In contrast, *'making fun of someone'* and *'speaking hurtful words to someone'* are the less severe items on the aggression scale. This analysis provides additional support for the reliability of the measures. Both scales have high values of item separation and item reliability, indicating that the scales are able to distinguish adolescents based on their latent trait. Furthermore, the set of items provides abundant information for people along a full range of latent trait levels, confirming the appropriateness of the survey to measure aggressive and delinquent behaviour. However, the level of aggression of the adolescents is low in comparison to the severity of the items. Half of the adolescent have insufficient aggression to have committed one of the less severe behaviours (*'making fun of someone'*). The same is observed with the delinquency scale, where less than 1% of the adolescents show levels of delinquency that enable them to commit the more severe items. It seems that the adolescents sampled are too youthful to have had the opportunity to commit these two different types of aggressive behaviours in their lifetime. Consequently, a future application of this survey could include a wider range of ages of the population.

After controlling for measurement error, results from the multilevel Rasch model showed that in Medellin the mean probability of an adolescent being engaged in aggression and delinquency is 7.0% and 0.3% respectively. Results from the multivariate model reveal a correlation between the scales of 0.83, suggesting that adolescents with high levels of aggression also tend to have high levels of delinquent behaviour. Although the scales are quite highly correlated there is no evidence that the two dimensions of aggressive behaviour are indistinguishable and that they should be collapsed into one single dimension. Following Cheong et al. (2000) a high correlation among latent scales of aggressive behaviour is a necessary but not sufficient condition to assert uni-dimensionality. It may also be that these two dimensions are differently related to individual, family and neighbourhood characteristics.

The primary goal of this chapter is to measure individual latent traits of adolescent aggressive behaviour and to assess their psychometric properties. By using Item Response Theory models, two reliable and valid latent variables of aggressive behaviour are obtained. In the next chapter, the current two-level measurement model is extended to a three-level Rasch model, with items nested within adolescents within neighbourhoods, to develop aggressive behaviour scores for adolescents and neighbourhoods while controlling for measurement error.

Chapter 4. Measuring aggressive behaviour for adolescents and neighbourhoods

While Chapter Three is concerned with the measurement of individual aggressive behaviour, this chapter focuses on the simultaneous measurement of aggressive behaviour in neighbourhoods and adolescents. This chapter extends the two-level Rasch model to include random effects at the neighbourhood level. Consequently, the two-level Rasch model is now implemented as a three-level Rasch model, with items within individuals within neighbourhoods, to properly define an interval scale for both of the aggressive behaviour outcomes not only at the individual level but also at the neighbourhood level.

By applying the Raudenbush and colleagues (2003) strategy, the analysis in this chapter develops high quality scales of aggressive behaviour, assesses their psychometric properties at the individual and neighbourhood level and evaluates the nature of the variation between individuals and neighbourhoods. Given that the survey participants are clustered within a geographical area and that the number of adolescents per neighbourhood varies considerably (from 1 to 48), the Raudenbush methodology is extended to include spatial effects. This development aims to improve the precision and validity of the aggressive behaviour measures by incorporating additional spatial dependency between neighbourhoods, whereby individuals are conceived as 'belonging' to their own neighbourhood and, additionally, to surrounding neighbourhoods (Lawson et al., 2003). In addition, the distributional assumptions of the model are assessed and alternative latent models are used when the latent trait does not necessarily follow the commonly assumed Normal distribution. The latent class model relaxes the distributional assumptions by fitting a model with a discrete classification of the adolescents and/or neighbourhoods into groups with distinctive patterns of aggressive behaviour, rather than as a continuous latent trait.

This chapter is organized as follows. First, the methodological framework to extend the two-level Rasch model to a three-level model and to a spatial multiple-membership model is detailed. Next, using the two aggressive behaviour dimensions, latent trait models and latent class models are estimated to obtain valid measures of aggressive behaviour at both individual and neighbourhood levels. Particular attention is paid to evaluating model assumptions in order to choose the 'best' latent model needed to represent the Medellin data. Four models are estimated in this chapter:

1. Three-level Rasch model in which individuals are nested within neighbourhoods with separate estimation of aggression and delinquency latent traits;
2. Three-level multivariate Rasch model, which retains the same structure but simultaneously models the two dimensions of aggression and delinquency;
3. Spatial multiple membership Rasch model which additionally allows spatial clustering of aggression and delinquency traits; and
4. Three-level latent class model in which the Normality requirement is relaxed.

Figure 17 outlines the procedures deployed in this chapter as a set of steps. This follows on from Figure 2 in Chapter Three which outlined how to create uni-dimensional scales. The figure also specifies the software environment in which a particular step is undertaken. This chapter ends with models estimating both continuous and categorical aggressive behaviour scales, which will be used in Chapter Six as response variables to be predicted by individual and neighbourhood-level characteristics using both the multivariate multilevel Rasch model and the multilevel latent class model.

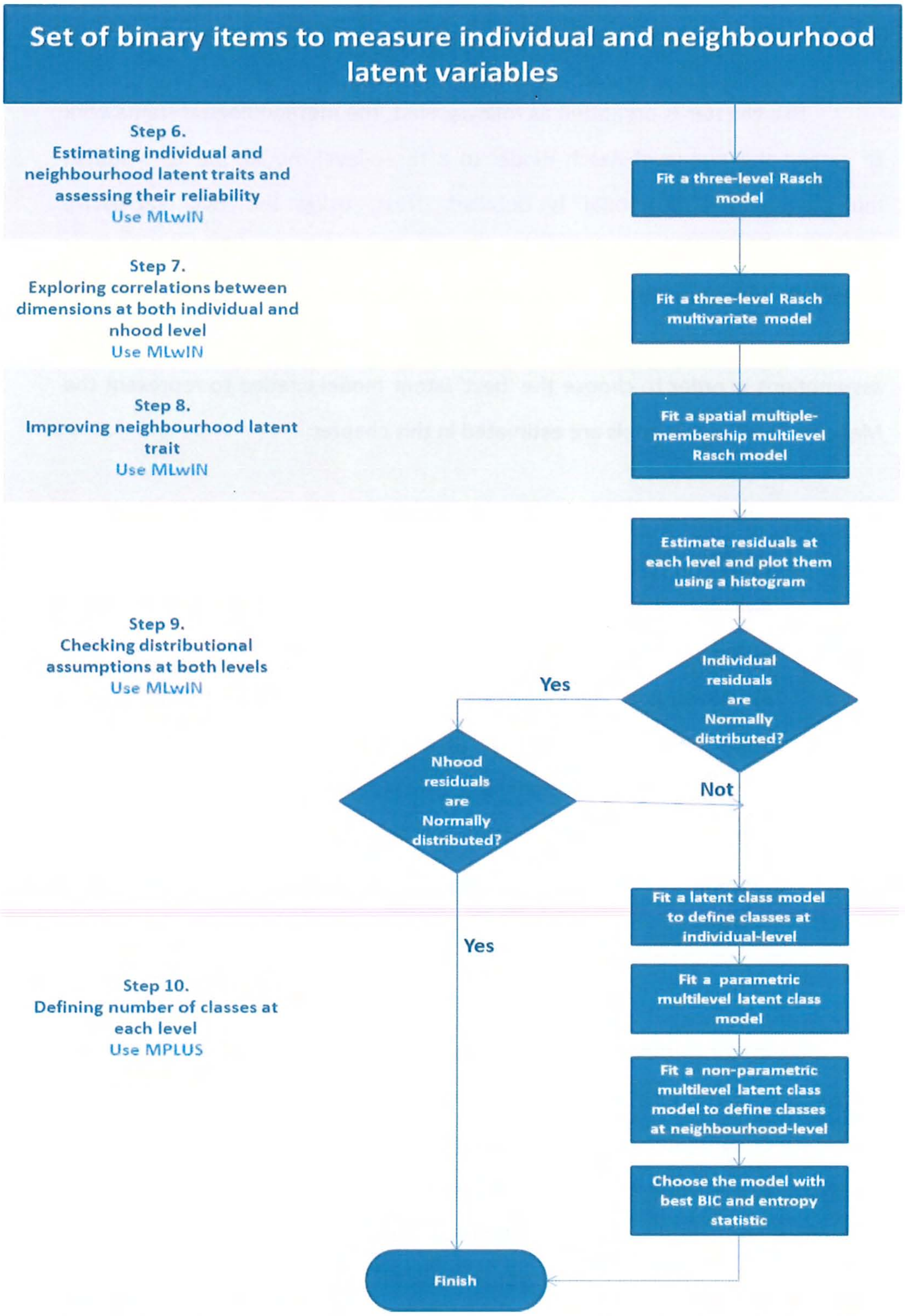


Figure 17 Steps to perform a multilevel Rasch analysis to estimate individual and neighbourhood latent variables

The Rasch model as a three-multilevel model

So far, the Rasch analysis has been confined to estimating the aggression and delinquency score at the individual level. The analysis is now extended to a three-level Rasch model with items nested within persons and within neighbourhoods, to develop aggressive behaviour scores for adolescents and neighbourhoods while controlling for measurement error. This multilevel three-level Rasch model is specified as follows:

$$y_{ijk} \sim Binomial \ (Denom_{ijk}, \pi_{ijk})$$

$$\log e\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \beta_0 x_{0ij} + \beta_1 x_{1ijk} + \ldots + \beta_{i-1} x_{i-1jk} + u_{0jk} x_{0ij} + v_{0k} x_{0ijk};$$

$$u_{0jk} \sim N(0, \sigma^2_{u0}); v_{0k} \sim N(0, \sigma^2_{v0}); \qquad Var(y_{ijk} \mid \pi_{ijk}) = \sigma^2_e \pi_{ijk}(1-\pi_{ijk})$$

where y_{ijk} is a binary response for item *i* as reported by adolescent *j* in neighbourhood *k*. Denom is the number of trials of the binomial distribution, here a set of 1, π_{ijk} is the estimated probability of saying 'yes' to item *i* for person *j* in neighbourhood *k.* The x_{ijk} terms are indicator variables representing the *i*-1 items in the scales as reported for adolescent *j* in neighbourhood *k,* where the not included item serves as the reference item. Again, each dummy is centred around its mean and therefore, β_0 represents the log-odds of a *typical* adolescent on his/her latent trait score responding affirmatively to a typical aggressive behaviour item in the typical neighbourhood. There are now two higher-level random terms: u_{0jk}, which is the latent trait of aggressive behaviour for person *j* in neighbourhood *k*, and v_{0k}, which is the neighbourhood-underlying propensity for aggressive behaviour on the logit scale. The differential latent trait is summarised by the variance σ^2_{u0}, while the neighbourhood differential is summarised by σ^2_{v0}. The level 1 variation represents the variation in the observed binary outcome y_{ijk}, given the estimated probability of saying 'yes' (π_{ijk}). This is determined by σ^2_e, which is constrained to 1 as it is a Bernoulli distribution. The key feature of this model is that the higher level variance has now been decomposed into two parts; the between neighbourhood and the within neighbourhood between adolescent variation.

Just as with the standard two-level Rasch model, it is important to estimate measures that help interpret model coefficients and to summarise their reliability. Consequently a range of procedures are considered specifically for the three-level model which specifies neighbourhoods at the highest level.

Interpreting the size of the neighbourhood effects: the intra-cluster correlation and the Median Odds Ratio

Using the multilevel formulation of the one-parameter Rasch model, the total variance of the underlying propensity of aggressive behaviour can be partitioned into different components of variation and describe the degree of similarity in the responses between two randomly chosen units at the same level. That is, the statistic intra-cluster correlation coefficient or intra-class correlation coefficient (ICC) can be computed (Goldstein et al., 2002). This statistic, which is commonly represented by ρ, can be expressed as the percentage of variation in a data set that is attributed to the particular level, out of the total variation (Kawachi and Subramanian, 2006). Thus, the VPC is defined as:

Level 2 $ICC = \sigma_u^2/(\sigma_v^2 + \sigma_u^2 + \sigma_e^2)$, which indicates the percentage of variance due to differences between adolescents in different neighbourhoods, or, the degree of similarity between responses for the same adolescent, and

Level 3 $ICC = \sigma_v^2/(\sigma_v^2 + \sigma_u^2 + \sigma_e^2)$, which indicates the percentage of variance due to differences between neighbourhoods, or the correlation between responses in the same neighbourhood.

In the logistic model, the level-1 variance σ_e^2 is expressed on the probability scale while the other higher level variances are expressed on the logistic scale (Merlo et al., 2006). Given these different scales, the calculation of the ICC is more difficult than in standard linear models. To overcome this, it is common to adopt a latent-variable approach which assumes the presence of a threshold continuous latent variable representing the observed binary responses. Thus, in this logit model there is an underlying standard logistic distribution with a variance of $\frac{\pi^2}{3} = 3.29$ (Goldstein et al., 2002, Snijders and Bosker, 1999). Consequently, in the computation of the ICC, the value of the level-1 variance is set to this value.

However, according to recent epidemiological and social research literature, the interpretation of the ICC for binary responses is problematic. As Duncan and Raudenbush (1999) demonstrate, apparently small proportions of the variance between neighbourhoods are, in fact, effect sizes that are considered quite large. Moreover, Merlo, Chaix et al. (2006) have argued that the ICC does not provide sufficient insight about the importance of the neighbourhoods for understanding the outcome of interest. One suitable alternative to quantify effects and ultimately provide a better understanding of their size is to calculate the Median Odds Ratio (MOR) (Merlo et al., 2006). The MOR takes advantage of the appealing properties of the logistic regression and translates the higher-level variances into an odds ratio scale, providing a more consistent and better interpretation. MOR quantifies the variation between neighbourhoods by conceptually randomly choosing and comparing any two adolescents from two different neighbourhoods. It can be interpreted as the increased risk of aggressive behaviour that, on average, an adolescent would have if s/he moves to another neighbourhood with higher risk of aggressive behaviour (Larsen and Merlo, 2005).

The MOR is estimated as a function of the neighbourhood-level variance as:

$$MOR = \exp(0.95\sqrt{(2 * \sigma^2_{v0})} * 0.6745)$$

$$\approx \exp(0.95\sqrt{\sigma^2_{v0}})$$

where 0.6745 is the 75th percentile of the cumulative distribution function of the standard Normal distribution. The MOR is always greater than or equal to 1. A value of 1 indicates that there are no differences between neighbourhoods. Larger values than 1 indicate variation at the neighbourhood level, and this is interpreted as an odds ratio. The credible interval of the MOR (Bayesian confidence intervals) can be derived from the monitoring chain of the MCMC estimates and from the above equations.

Reliability of the aggressive behaviour estimates

This three-level specification of the Rasch model can be used to estimate the reliability of the scale, to discriminate among adolescents within a neighbourhood and among adolescents in different neighbourhoods.

Reliability at the person level

The formula for calculating the reliability of a specific level-2 unit (adolescents) in a three-level logit model is given by Cheong and Raudenbush (2000) as:

$$Reliability_{jk} = \frac{\sigma^2_{v0} + \sigma^2_{u0}}{\sigma^2_{v0} + \sigma^2_{u0} + \frac{\sigma^2_e}{n_{jk}(\bar{\pi}_{jk}(1-\bar{\pi}_{jk})}}$$

Thus, $Reliability_{jk}$ refers to the internal consistency of the aggressive behaviour measure for adolescent *j* in neighbourhood *k;* the level-1 variance that is associated with the Bernoulli weight is represented by σ^2_{e0}, which is the value 1.[2] The number of items on aggressive behaviour rated for adolescent *j* in neighbourhood *k* is given by n_{jk}, and the variance for each adolescent based on the predicted average proportion of affirmative answers, $\bar{\pi}_{jk}$, is given by $\bar{\pi}_{jk}(1 - \bar{\pi}_{jk})$ (Gelman and Hill, 2007).

Reliability at person level conditioning on neighbourhoods

In a later paper, Raudenbush *et al.* (2003) provide a variant on the measure of person reliability that conditions on neighbourhood membership. The reliability for each person is given by:

$$Reliability_{jk} = \frac{\sigma^2_{u0}}{\sigma^2_{u0} + \frac{\sigma^2_e}{n_{jk}(\bar{\pi}_{jk}(1 - \bar{\pi}_{jk})}}$$

Thus, $Reliability_{jk}$ is the internal consistency of the aggressive behaviour measure for adolescent *j;* σ^2_{e0} is the level 1 variance that is associated with the Bernoulli weight that is the value 1; n_{jk} is the number of items on aggressive behaviour rated for adolescent *j* in neighbourhood *k;* $\bar{\pi}_{jk}(1 - \bar{\pi}_{jk})$ is the variance for each adolescent based on the predicted average proportion of affirmative answers, $\bar{\pi}_{jk}$. Notice that there is no between neighbourhood variance in this equation, so that the level-2 variance (adolescent level) is estimated for individuals within neighbourhoods.

[2] It is not 3.29 the variance of the standard logistic distribution that was explained previously. Here, the formula of Cheong and Raudenbush (2000) is used where the level-1 variance is $\sigma^2_e(\hat{\pi}_{ijk}(1 - \hat{\pi}_{ijk}))$ and not simply σ^2_e. In a later paper the level-1 variance is estimated rather than constrained (Raudenbush et al. 2003). This is done to allow for local dependence in the items; however, this is not admissible with Bernoulli data (Gelman and Hill 2007) and the level-1 variance is constrained to 1 when Bernoulli data are analysed.

Reliability at neighbourhood level

The reliability at the neighbourhood level is the ratio of the variance of the latent 'true' neighbourhood means to the variance of the estimates:

$$Reliability_k = \frac{\sigma_{v0}^2}{\sigma_{v0}^2 + \frac{\sigma_{u0}^2}{J_k} + \frac{\sigma_e^2}{n_k J_k (\bar{\pi}_k (1 - \bar{\pi}_k)}}$$

Thus, $Reliability_k$ is the internal consistency of the aggressive behaviour measure for neighbourhood *k,* where σ_{e0}^2 is the level-1 variance that is associated with the Bernoulli weight, that is the value 1, the number of adolescents sampled within neighbourhood k is given by J_k and, the average number of items per adolescent in neighbourhood *k* is represented by n_{k}. Finally, $\bar{\pi}_k(1 - \bar{\pi}_k)$ is the variance based on the predicted average proportion of affirmative answers in neighbourhood k, $\bar{\pi}_k$. As can be seen, the neighbourhood's reliability depends on the intra-neighbourhood correlation; the number of adolescents sampled, the number of items per trait, and the item severities, (through $\bar{\pi}_k$). The approximation is exact when all participants provide responses on all items.

Both person and neighbourhood reliabilities can range from 0 to 1. A reliability coefficient of 0.80 indicates that 20% of the variability in test scores is due to measurement error. In the test reliability literature the following values are often given as guides to interpret the results: > 0.8 excellent reliabilities, 0.7 to 0.8 very good, 0.6 to 0.7 satisfactory, and <0.6 suspect (Mujahid et al., 2007).

Interpreting the results from the three-level model

The three-level multilevel model is fitted separately to the Medellin data with 1,686 adolescents and 103 neighbourhoods for the two sets of items representing aggression and delinquency. The models are estimated using MCMC estimation procedures in MLwiN 2.22 (Rasbash et al., 2000) which are known to give high quality estimates when there are relatively few lower level units in each higher level unit, as here (Rodriguez, 2008). The length of the monitoring chain used for this analysis is 50,000, with a burn-in of 5,000 simulations; all chains of the estimates have an information content equivalent to at least 500 independent draws.

The results of the fixed part relating to the item estimates are quite close than those described in Chapter Three. However, their interpretation is somewhat different as account is now taken of the neighbourhood level. According to the results, the expected logit of answering affirmatively an aggression item for a typical adolescent in a typical neighbourhood is -2.47. The corresponding median probability is 7.8% (95% CI 6.7% - 9.2%). The logit of endorsement of a delinquency item for a typical adolescent in a typical neighbourhood is -5.99, the corresponding median probability is 0.3% (95% CI 0.1% - 0.5%). The estimates of the higher-level variances of the random part for the aggression and delinquency scales are shown in Table 10. There is significant variation between adolescents and neighbourhoods for both scales ($p< 0.001$). Using the ICC formula, it is estimated that seven percent of the total variation in the prevalence of aggression and 14 percent for the delinquency occur at the neighbourhood level. So, these results show that there is sizeable neighbourhood geography for both types of aggressive behaviour, being higher for the delinquency, and, consequently, that the multilevel model is essential for estimating contextual variation on both aggressive behaviour scales. These results are confirmed by the MOR neighbourhood measures. For the aggression scale, the MOR at the neighbourhood level is equal to 1.84 (95% CI 3.33 - 3.99) and for the delinquents equal to 3.40 (95% CI 9.00 - 19.81). This indicates that if an adolescent moves from a neighbourhood with low levels of aggression/delinquency to one with high aggression/delinquency, his/her individual odds is around two/three times bigger than if s/he stays in a lower risk neighbourhood. The estimates of reliability of the adolescent and neighbourhood means are also shown in Table 10. For the aggression scale, the average reliability across adolescents is 0.71 and across adolescents within a neighbourhood is 0.67. For the delinquency scale, the estimated values are much lower at 0.21 across adolescents and 0.19 across adolescents within a neighbourhood. This indicates that aggressors can be discriminated across the city and within a neighbourhood reliably, which is not the case for the delinquents. The average reliability across neighbourhoods is markedly higher for both scales, with a value of 0.94 for the aggression scale and 0.91 for the delinquent. Taking into consideration that the reliability of the neighbourhood measures is a function of the between and within neighbourhood variances, as well as the number of individuals within each neighbourhood (Mujahid et al., 2007), the observed higher values are due to the high variation found across neighbourhoods. In contrast, the low reliabilities of the individual measures of delinquency may be due to the low number of items making up that scale. In summary, at the neighbourhood-level it is possible to distinguish reliably between areas on both scales, but at the adolescent-level it is only possible to do this for aggression and not for delinquency.

Table 10 Random component estimates from the multilevel multivariate model for the aggressive behaviour scales

Random Part	Variance	Std. err.	95% Credible Interval	MOR	MOR 95% Credible Interval	Reliability
Adolescent						
Aggression	1.84	0.13	(1.61 - 2.12)			0.71 and 0.67*
Delinquency	7.26	1.16	(5.35 - 9.88)			0.21 and 0.19*
Neighbourhood						
Aggression	0.41	0.11	(0.25 - 0.65)	1.84	(1.61 - 2.15)	0.94
Delinquency	1.66	0.55	(0.86 - 3.00)	3.40	(2.41 - 5.18)	0.91

*Reliability conditioning on neighbourhood membership
The variance parameters are the medians of 100,000 and 50,000 chains, with a burn-in of 500. The limits of the 95 percent credible intervals are 2.5% and 97.5% points of the distribution of the chains.

The Rasch model as a multilevel multivariate model

In the same manner as Chapter Three, the three-level Rasch model can be extended to a multivariate model to analyze jointly the two dimensions of aggressive behaviour and their covariance (and therefore correlation). Importantly the correlation can now be assessed at both the individual and neighbourhood level (Raudenbush et al., 2003). In this extended model, the log-odds for the aggressive behaviour dimensions for adolescent *j* in neighbourhood *k* is specified as:

$$y_{ijk} \sim Binomial\ (Denom_{ijk}, \pi_{ijk})$$

$$\log e\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = D_{AGijk}\,(\beta_{0AG} + \beta_1 x_{1ijk} + \beta_2 x_{2ijk} + \ldots + \beta_{i-1} x_{i-1jk} + u_{AG0Jk} x_{0ij} + v_{AG0k} x_{0ijk}) +$$

$$D_{DEijk}\,(\beta_{0DE} + \beta_1 z_{1ijk} + \beta_2 z_{2ijk} + \ldots + \beta_{i-1} z_{i-1jk} + u_{DE1jk} x_{0ij} + v_{DE1k} x_{0ijk})$$

$$u_{AG1jk} \sim N(0, \Omega_u) \qquad \Omega_u = \begin{bmatrix} \sigma^2_{u1} & \\ \sigma_{u12} & \sigma^2_{u2} \end{bmatrix}$$
$$u_{DE1jk} \sim N(0, \Omega_u)$$

$$v_{AG1k} \sim N(0, \Omega_v) \qquad \Omega_v = \begin{bmatrix} \sigma^2_{v1} & \\ \sigma_{v12} & \sigma^2_{v2} \end{bmatrix}$$
$$v_{DE1k} \sim N(0, \Omega_v)$$

$$Var\ (y_{ijk} \mid \pi_{ijk}) = \sigma^2_e \pi_{ijk} (1 - \pi_{ijk})$$

where, y_{ijk} is again the set of binary responses for item *i* as reported by adolescent *j* in neighbourhood *k*. Denom is a set of 1. The estimated probability of saying 'yes' to item *i* for person *j* in neighbourhood *k* is given by π_{ijk}. The two terms, $D_{AG\,ijk}$ and $D_{DE\,ijk}$, are indicator variables for the aggression and delinquency scale. The items are related to each of the scales and are also represented by x_{ijk} for the aggression scales and by z_{ijk} for the delinquency scale. Each dummy is again centred around its mean, and therefore, β_{0AG} is interpreted as the log-odds of a *typical* adolescent on his/her latent trait score responding affirmatively to a typical aggression item in the typical neighbourhood. Equivalently, β_{0DE} is interpreted as the log-odds of a *typical* adolescent on his/her latent trait score responding affirmatively to a typical delinquency item in the typical neighbourhood. The adolescent and neighbourhood random effects for the aggression and delinquency scale are given by u_{AG0Jk} and v_{AG0k} and by u_{DE1jk} and v_{DE1k} respectively. These are assumed to be Normally distributed with zero means, and variances at the adolescent-level given by σ^2_{u1} for the aggression scale, and, σ^2_{u2} for the delinquency scale respectively, and a covariance term σ_{u12} . At the neighbourhood-level, the variance terms representing the aggression and delinquency scales are given by σ^2_{v1} and σ^2_{v2} respectively, and the covariance term modelling their correlation by σ_{v12} . Finally, $\sigma^2_e \pi_{ijk} (1 - \pi_{ijk})$ represents the level 1 variance that is associated with the Bernoulli weight, which is constrained to 1.

The results of this model, estimated by MCMC procedures using MLwiN v 2.22, are shown in Table 11. For this model a burn-in of 500 iterations is used, with monitoring for a further 200,000 iterations. Again, results of the random terms at the adolescent-level are quite close to those showed in Table 10. According to the results, the estimated covariance between neighbourhoods is 0.67 while the estimated covariance between adolescents is 3.26. The estimated correlation of the two scales at the neighbourhood level is reasonably high at 0.80, while the correlation at the individual level is estimated to be slightly higher at 0.85. Thus, there is a strong tendency for both latent traits of aggression and delinquency to be strongly correlated at both the individual and neighbourhood level.

Table 11 Covariance component estimates from the multilevel multivariate model for the aggressive behaviour scales

Random Part	Variance	Std. Err.	95% Credible Interval
Adolescent			
Aggression	2.06	0.15	(1.79 - 2.36)
Delinquency	7.14	1.06	(5.28 - 9.41)
Covariance	3.26	0.29	(2.73 - 3.85)
Neighbourhood			
Aggression	0.40	0.10	(0.23 - 0.63)
Delinquency	1.77	0.54	(0.91 - 3.02)
Covariance	0.67	0.20	(0.34 - 1.12)

The variance parameters are the medians of 200,000 chains, with a burn-in of 500. The limits of the 95 percent credible intervals are 2.5% and 97.5% points of the distribution of the chains.

Figure 18 shows the distribution of the estimated traits at both individual and neighbourhood-level. Consistent with the results from the two-level Rasch model estimated in Chapter Three, the distribution of the individual scores derived from the multivariate three-level Rasch model also gave evidence of a skewed distribution for both scales, in particular for the delinquency scales where very few adolescents show higher latent trait scores. In contrast, the distribution of the neighbourhood scores more closely approximates a Normal distribution, but there is some evidence of negative skew for the aggression scale.

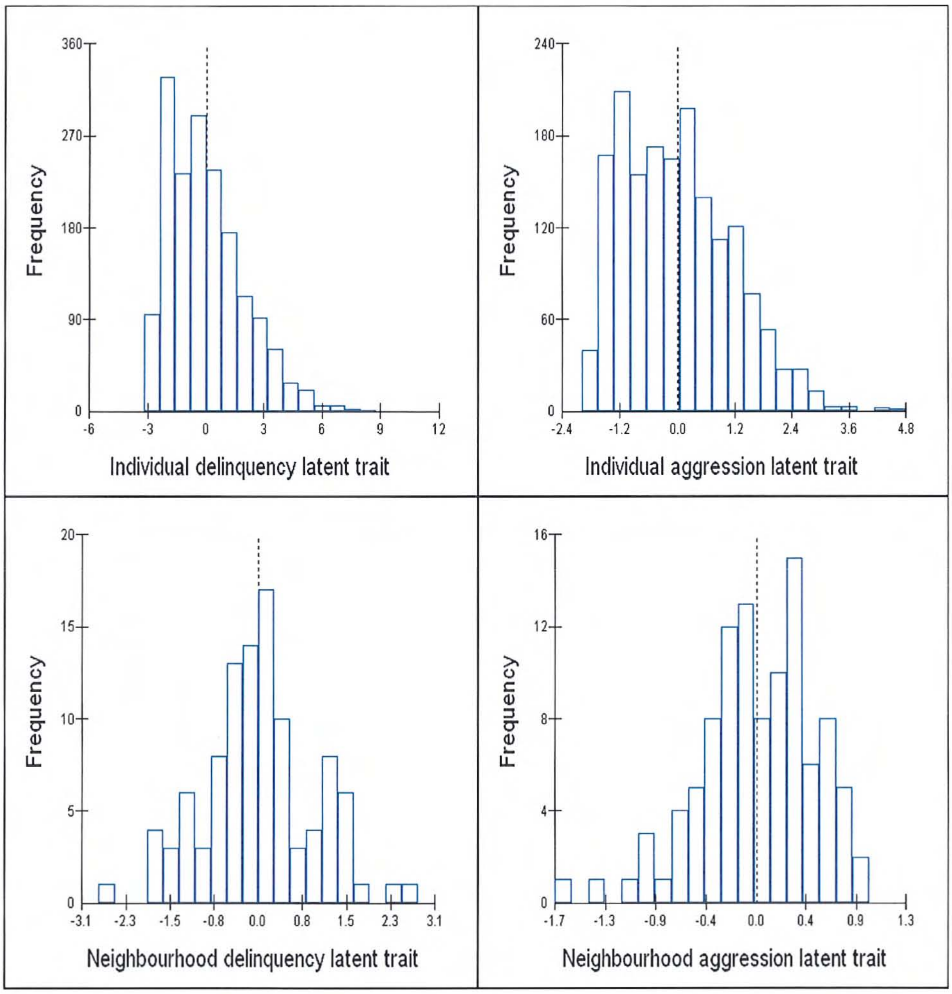


Figure 18 Frequency distribution of the estimated individual and neighbourhood aggressive behaviour scores. Medellin, 2007.

Figure 19 maps the neighbourhood logits of both scales. Many neighbourhoods falling within the highest tercile for the aggression scale are predominantly concentrated in the north and east part of the city (Figure 19a). This same pattern is observed in Figure 19b, which suggests the areas where the highest level of delinquency is found. Most of the neighbourhoods of the north side of the city fell within the highest tercile, with another cluster appearing on the east side of the city. Due to the high correlation between the two aggressive behaviour dimensions at neighbourhood level, it is clear from the maps that neighbourhoods with high level of aggression tend to have also high levels of delinquency.

Map A

Map B

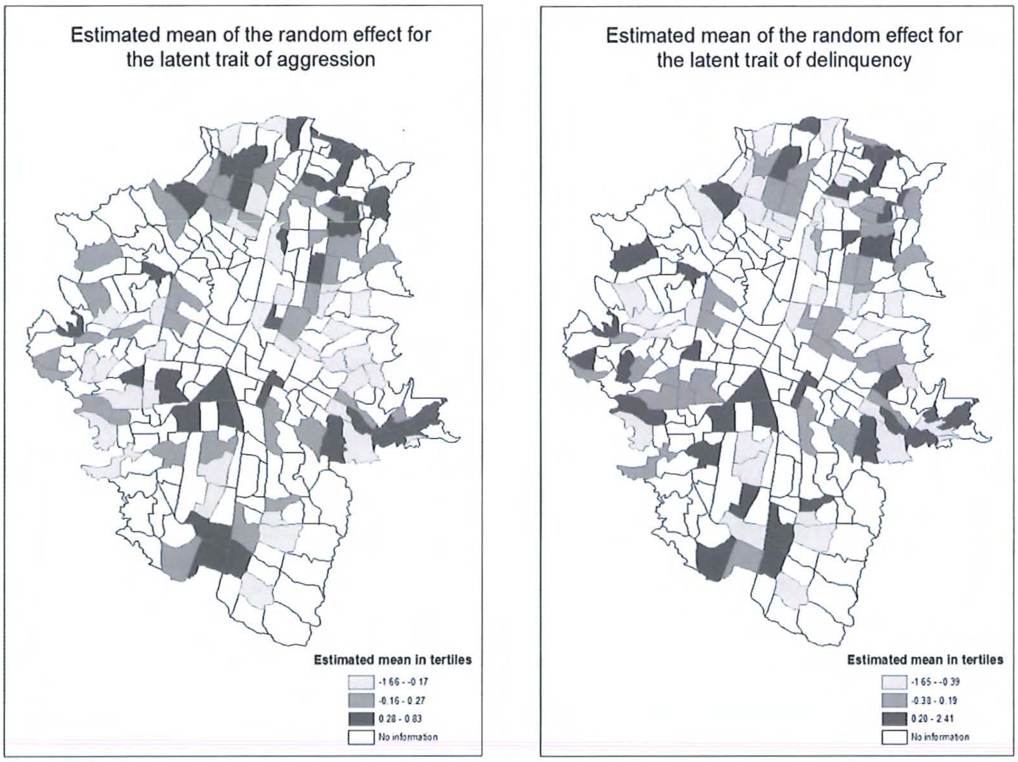


Figure 19 Estimated neighbourhood latent trait of the aggressive behaviour scales in terciles. Medellin, 2007

The Rasch model as a spatial multiple-membership multilevel model

The analysis up to this point has only used the information from the immediate neighbourhood to measure the level of aggressive behaviour, thereby ignoring the effects of surrounding areas. But, it may be more realistic to include additional effects from surrounding neighbourhoods. This can be achieved in a spatial multiple membership model that incorporates spatial structures, whereby individuals are conceived as 'belonging' to their own neighbourhood and additionally to surrounding neighbourhoods. Figure 20 shows the underlying structure of this situation (Browne, 2003, Lawson et al., 2003).

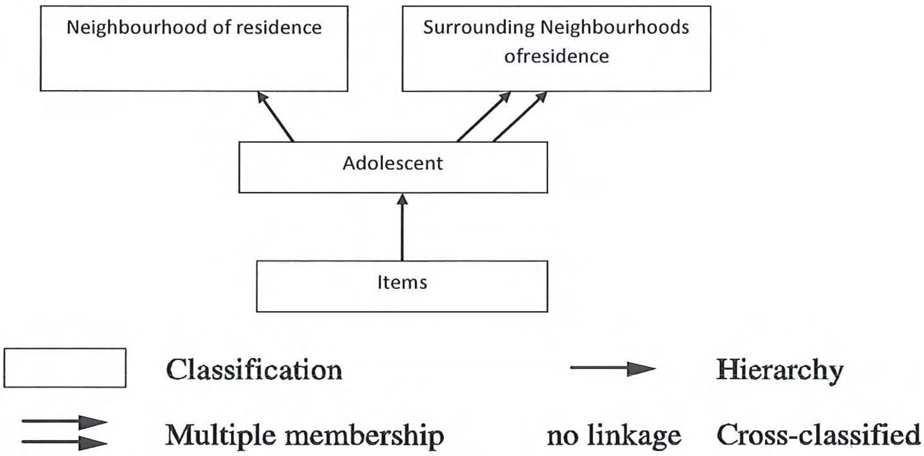


Figure 20. Underlying structure of the data in the spatial multiple membership framework

This model incorporates an additional random term which represents the multiple membership effect of surrounding neighbourhoods (Fielding and Goldstein, 2006). It is a multiple membership model as the adolescent is conceived as belonging to more than one neighbourhood. Consequently, in this model the higher-level random effects of each aggressive behaviour latent trait are made up of three components: 1) between adolescent effects; 2) aspatial between-neighbourhood effects; and 3) spatial neighbouring effects (from neighbourhoods that share common boundaries). This model in its multivariate form can be written as:

$$y_i \sim Binomial\ (Cons_i, \pi_i)$$

$$\log e\left(\frac{\pi_i}{1-\pi_i}\right) = D_{AGi}(\beta_{0AGi} + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_{i-1} x_{i-1} +$$

$$\sum_{j \in Neigbour(i)} w^{(4)}_{AG0ij} u^{(4)}_{OA1j} + u^{(3)}_{AG0Nhood(i)} x_{0ij} + u^{(2)}_{AG0Person(i)} x_{0ij}) +$$

$$D_{DEi}(\beta_{1DEi} + \beta_1 z_{2i} + \beta_3 z_{3i} + \ldots + \beta_{i-1} z_{i-1} +$$

$$\sum_{j \in Neigbour(i)} w^{(4)}_{DE1ij} u^{(4)}_{DE1j} + u^{(3)}_{DE1Nhood(i)} x_{0ij} + u^{(2)}_{DE1Person(i)} x_{0ij})$$

$$u^{(4)}_{AG0Neighbour(i)} \sim N(0, \Omega^{(4)}_u) \qquad \Omega^{(4)}_u = \begin{bmatrix} \Omega^{(4)}_{u0,0} & \\ \Omega^{(4)}_{u0,1} & \Omega^{(4)}_{u1,1} \end{bmatrix}$$

$$u^{(4)}_{DE1Neighbour(i)} \sim N(0, \Omega^{(4)}_u)$$

$$u^{(3)}_{AG0Nhood(i)} \sim N(0, \Omega^{(3)}_u) \qquad \Omega^{(3)}_u = \begin{bmatrix} \Omega^{(3)}_{u0,0} & \\ \Omega^{(3)}_{u0,1} & \Omega^{(3)}_{u1,1} \end{bmatrix}$$

$$u^{(3)}_{DE1Nhood(i)} \sim N(0, \Omega^{(3)}_u)$$

$$u^{(2)}_{AG0Person(i)} \sim N(0, \Omega^{(2)}_u) \qquad \Omega^{(2)}_u = \begin{bmatrix} \Omega^{(2)}_{u0,0} & \\ \Omega^{(2)}_{u0,1} & \Omega^{(2)}_{u1,1} \end{bmatrix}$$

$$u^{(2)}_{DE1Person(i)} \sim N(0, \Omega^{(2)}_u)$$

$$Var(y_{ijk} \mid \pi_{ijk}) = \sigma^2_e \pi_{ijk}(1 - \pi_{ijk})$$

The notation used here differs from the one given earlier and follows Browne, Goldstein and Rasbash (2001) as the model specification is not simply hierarchical. The new notation uses only one subscript *i* to represent the lowest level (item responses) and three classification indicators to represent the subscripts for the person (classification-2), neighbourhood (classification-3) and surrounding neighbours (classification-4) random effects. These three separate random effects influencing the logit of an affirmative response are given by $u^{(2)}_{DPerson(i)}$, $u^{(3)}_{DNhood(i)}$ and $u^{(4)}_{DNeighbour(i)}$ and are assumed to be Normally distributed, with mean of 0 and variance $\Omega^{(2)}_{u1,1}$, and $\Omega^{(4)}_{u}$. The covariance terms for the three classification levels are given by $\Omega^{(4)}_{u0,1}$, $\Omega^{(3)}_{u1,1}$ and $\Omega^{(2)}_{u0,1}$ respectively, and indicate the correlation between the two latent constructs at the spatial, aspatial and person levels. The superscript represent the classification number, which starts from 2 given that the lowest level (items) is considered as classification 1. The weight assigned to the neighbour random effect for neighbourhood k for adolescent j is given by $w^{(4)}_{ij}$. In this model the weights are constructed to sum to one ($\sum_{j\epsilon\, Nbour(i)} w^{(4)}_{ij} = 1$). If n_j refers the number of adjacent neighbours of neighbourhood i, then: $w^{(4)}_{i,j} = 1/n_j$ if neighbourhood i and j share a common boundary and, $w_{i,j}^{(4)} = 0$ otherwise (Fielding and Goldstein, 2006). The weights and the corresponding spatial adjacency matrix are created using the Adjacency for WinBUGS Tool (Upper Midwest Environmental Sciences Center, 2010). Finally, $\sigma_e^2 \pi_{ijk}(1-\pi_{ijk})$ is the level-1 variance associated with the Bernoulli weight, which is the value 1.

There are two reasons for using this spatial model. Firstly, substantively it allows the assessment of whether there are clusters of aggressive behaviour that are wider than the specific neighbourhood that the respondents live in. The second reason is to obtain improved estimation, and hence more reliable measurements. In this study, the number of adolescents ranges considerably, with some neighbourhoods having only 1 adolescent while others had 48. The spatial model 'pools' information across neighbourhood groupings. Consequently, poorly estimated neighbourhoods, those with few respondents, are potentially helped by the information contained in surrounding neighbourhoods. Thus, this model calculates precision-weighted estimates, and, where there is little information on a neighbourhood's specific latent trait, the resultant estimate will be shrunk back towards the mean of the neighbouring neighbourhoods in a form of spatial smoothing (Browne, 2003).

The results of the multivariate spatial multiple membership analysis find that the spatial variance and covariance terms are not statistically significant ($\Omega_{u0,0}^{(4)}$=0.17 se=0.11 for aggression, $\Omega_{u1,1}^{(4)}$=0.83 se=0.50 for delinquency and $\Omega_{u0,1}^{(4)}$=0.20 se=0.19 for the covariance term respectively). Comparisons of the DIC for both models also showed no substantial improvement of the model with the inclusion of the spatial neighbour terms, with DIC values of 11393.9 for the spatial neighbourhood effects model and 11395.4 for the model without spatial neighbour effects. The aspatial neighbourhood effects or aspatial effect – referring to the ordinary neighbourhood effect which does not have information in which part of the map the neighbourhoods are located– continue to show a large and highly significant variance for both scales ($\Omega^{(3)}_{u0,0}$=0.38 se=0.12 for aggression and $\Omega^{(3)}_{u1,1}$=1.61 se=0.58 for delinquency). This finding suggests that, in the Medellin data, there is a greater variability between neighbourhoods but not spatial clustering of the level of aggressive behaviour in adjacent neighbourhoods. This result may have been affected by the large number of neighbourhoods without any data. Whatever the cause, the spatial models represent no improvement on the standard multivariate model.

Multilevel latent class analysis

All the models that have so far been fitted to the Medellin data in this chapter and the last are based on the assumption that higher level terms follow a Normal distribution. However, as seen in Figure 18, there is evidence that this is not the case, especially at the individual level. This non-fulfilment of the assumption could result in inferential error when predictor variables are included. In this section a latent-class formulation is used which allows a discrete distribution for the random effects instead of a continuous scale for aggressive behaviour. Thus individuals may be grouped into distinct categories or cases, such as low, medium and high. The aim is to determine the number of categories and to categorize the adolescents into one of these different groups. The end result is a probability of group membership which can be subsequently modelled in terms of individual and neighbourhood predictors.

This latent class model can analyze three-level data structures, with items nested within individuals who are in turn nested within neighbourhoods (Vermunt, 2003b). The multilevel specification allows individual-level latent class intercepts to vary across neighbourhoods and thereby examines whether the probability of an individual belongs to one of the aggressive behaviour classes is different across neighbourhoods. This multilevel specification allows parametric or non-parametric random effects. In the former, the latent classes are discrete at individual-level but the trait for each category is continuous at neighbourhood-level. In the latter, the distribution is treated as discrete at both levels (Vermunt, 2003a, Henry and Muthén, 2010).

As pointed out by Vermunt, a non-parametric approach (either at level-2 or at level-3) does not mean 'distribution free' (Vermunt, 2003a). Indeed, the Normal distribution assumption is replaced by a multinomial distribution assumption in the form of a histogram, where non-Normality is allowed. This is best illustrated in Figure 21. The left side shows a resulting latent trait distribution which is clearly not Normally distributed. The right side of the figure shows a non-parametric distribution resulting from the discretization of the continuous distribution into a finite number of 'mass points' or 'points of support' (Vermunt, 2003a, Jen et al., 2010). According to Vermont, this 'mixing' distribution is obtained by increasing the number of masses until a saturation point is reached (Vermunt, 2003a). In practice, however, it has been demonstrated that relatively few latent classes are required to approximate even complex continuous distributions (Jen et al., 2010).

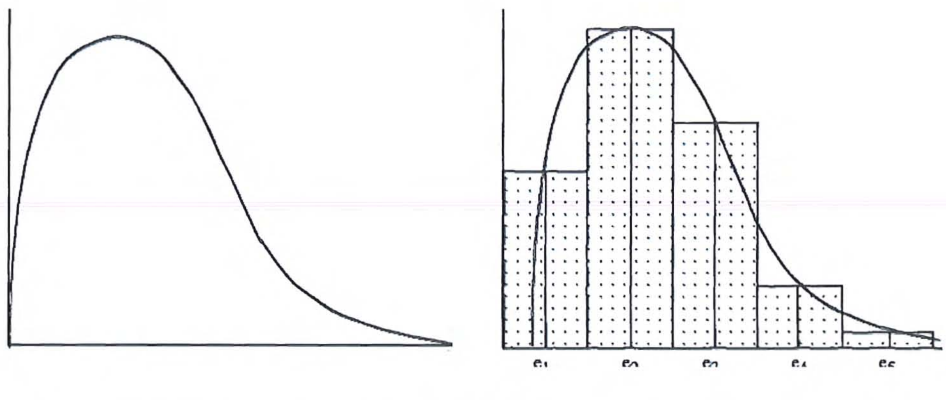


Figure 21 Approximating a continuous distribution to a discrete distribution. Adapted from Nagin and Land (1993)

In the case of the multilevel latent class approach with binary items and parametric random effects, the model can be written as (Johnston et al., 2009):

$$E(logit(y_{ijk})) = \sum_{c=1}^{G} \beta_0^{(c)} z_{jkc} + \mu_{jk}^{(c)} + v_k +$$

$$\mu_{jk}^{(c)} \sim N(0, \sigma_\mu^{2(c)}), v_k \sim N(0, \sigma_v^2)$$

$$z_{jkc} = \begin{cases} 1, if\ g_{jk} = c, \\ 0, if\ g_{jk} \neq c \end{cases}$$

where Y_{ijk} is the observed item response for item *i* of an adolescent *j* nested in neighbourhood *k*. The superscript *c* indexes specific level-2 latent classes or groups, which can be from one to G; $\beta_0^{(c)}$ is the intercept of the level-2 latent classes; z_{jkc} is an unobserved indicator of group membership, which is coded as 1 if adolescent *j* from neighbourhood *k* is in group *c* and 0 otherwise. There are three random terms summarizing the unexplained variation of the latent classes: level-1 is as always a Binomial distribution; $\mu_{jk}^{(c)}$ is the within-neighbourhood, between adolescent residual term for each group and v_k is the between-neighbourhood residual difference on the continuous logit scale. Both higher level terms are assumed to have a Normal distribution with a mean of zero and variances, $\sigma_\mu^{2(c)}$ and σ_v^2 respectively. The superscript *c* in the variances terms allows each group of adolescents to have a different degree of residual variability (Johnston et al., 2009).

The general structure of this parametric approach is best illustrated in Figure 22 using the approach of Muthén (Henry and Muthén, 2010). The figure displays an example of parametric multilevel latent class model with items nested within individuals nested in neighbourhoods, with three individual-level latent groups (C). In the model at the individual-level the filled circles represent the random means for the individual-level latent classes (given that c=3, there are 3 – 1 = 2 random means). These random means are referred to as C#1 and C#2 in the neighbourhood-level model. In this specification, C#1 and C#2 are continuous latent variables that vary across neighbourhoods. That is, the means from the individual-level latent classes are allowed to vary across neighbourhoods. The arrow that interconnects these latent variables indicates that these continuous between latent variables are potentially correlated with one another.

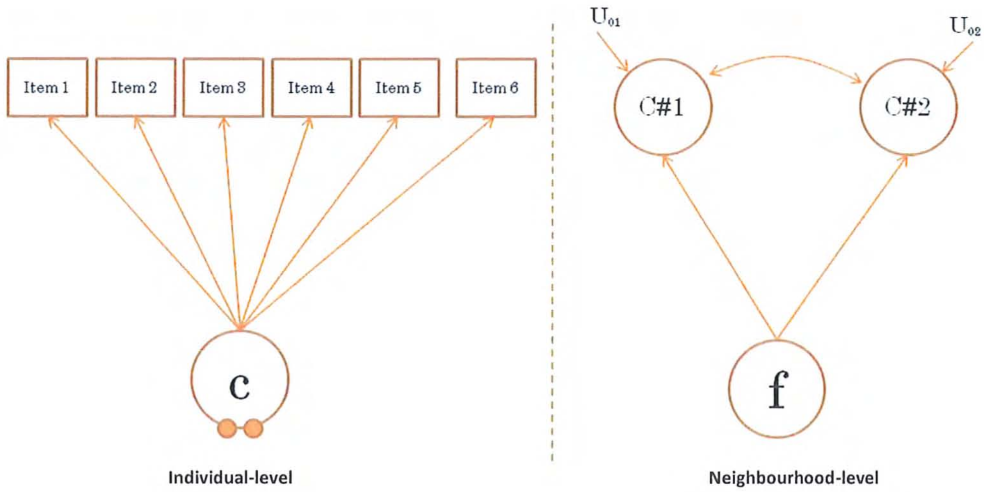


Figure 22 Multilevel latent class model with three individual-level latent classes under the parametric approach. Adapted from Henry and Muthén (2010)

The multilevel latent class approach with non-parametric random effects additionally allows a finite number of neighbourhood-level latent classes that capture the individual-level variability in the distribution of each individual-level latent class membership probabilities (Henry and Muthén, 2010). Formally, the model is written as:

$$\mathrm{E}(logit(y_{ijk})) = \sum_{c=1}^{G} \beta_0^{(c)} z_{jkc} + \sum_{d=1}^{H} \beta_0^{(d)} z_{kd} + \mu_j^{(c)} + \upsilon_k^{(d)}$$

$$z_{jkc} = \begin{cases} 1, if\, g_{jk} = c, \\ 0, if\, g_{jk} \neq c \end{cases}$$

$$z_{kd} = \begin{cases} 1, if\ g_k = d, \\ 0, if\ g_k \neq d \end{cases}$$

$$\mu jk(c) \sim N(0, \sigma_\mu^{2(c)}),\, \upsilon_k^{(d)} \sim N(0, \sigma_\upsilon^{2(d)})$$

where d indexes the value of neighbourhood k on the latent class variable defining the discrete mixing distribution, which can be from one to H; $\beta_0^{(d)}$ is the intercept of the neighbourhood-level latent classes or groups; z_{kd} represents an unobserved indicator of neighbourhood group membership, which is coded as 1 if neighbourhood k is in group k and 0 otherwise. As can be seen from the equations, each of the neighbourhood-level groups is allowed to have its own variance ($\sigma_v^{2(d)}$), as is each of the individual-level groups ($\sigma_\mu^{2(c)}$).

Figure 23 presents an example of this approach for a three individual-level latent group situation. The difference here is that the random means from the individual-level latent classes that are varying across the neighbourhood-level are specified to define neighbourhood latent classes, labelled as CB in Figure 23.

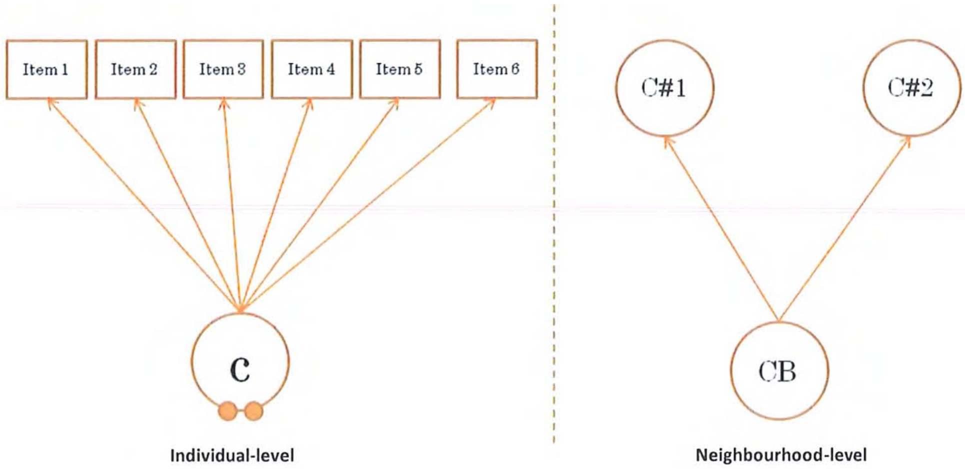


Figure 23 Multilevel latent class model with three individual-level latent classes under the non-parametric approach. Adapted from *Henry and Muthén* (2010)

Latent class analysis for items defining the aggression scale

To determine the number of latent classes at both levels, the four-step procedure suggested by Lukociene and Vermunt (2010) and by Henry and Muthén (2010) is used. Step 1, the number of adolescent-level latent classes is determined ignoring the multilevel structure. Step 2, fixing the number of adolescent-level latent classes to the value of step 1, a parametric model is specified to account for the nested structure of the data. Step 3, by fixing the number of adolescent-level latent classes to the value of step 1, the number of neighbourhood-level latent classes is determined by increasing the number of latent classes, stopping when the fit of the model no longer improves. Step 4, the number of adolescent-level latent classes is confirmed by fixing the number of neighbourhood-level latent classes to the value of step 2 and the adolescent-level latent classes is determined by increasing the number of latent classes again until the model fit no longer improves. The Bayesian Information Criterion is used to assess the best fitting model. Simulation evidence reported in Lukociene and Vermunt (2010) suggests that BIC detects very well the true number of latent classes when the neighbourhood-level sample size is large enough. An additional measure commonly used to select the optimal number of latent classes is the entropy statistic, which is a standardised measure of how accurately adolescents are classified into the groups. Values range from 0 to 1, with higher values indicating better classification (Murphy et al., 2007). The MPLUS v6.11 software (Muthén and Muthén, 1998-2010) is used to apply this procedure, first to the aggression scale; and then to the delinquency scale.

Table 12 shows the BIC for the sequence of latent class models that are estimated for the 10 items defining aggression. According to the results for the model without higher-level random effects, a solution with three latent classes suffices (Model 1). Subsequently, the nested structure of the data is taken into consideration, leading to an improvement on the three-class solution (Model 2). The four-class solution also shows a low BIC in comparison with the three-class solution but the entropy value (<0.70) indicates that the model has difficulty in distinguishing between adolescents among the four classes. The inclusion of two and three neighbourhood-level classes at the neighbourhood level does not improve the BIC of the parametric approach (Model 3 and Model 4). In this model, it is not necessary to undertake the last step of the Lukociene and Vermunt (2010) strategy to re-confirm the number of adolescent-level latent classes, given that there is no evidence of the presence of neighbourhood-latent classes. In conclusion, the results confirm that a three-class solution at adolescent level and two continuous latent neighbourhood random effects best represents the aggression data.

Table 12 Sequential model comparisons for the aggression latent trait scale

Model	Specification	Aggression scale			
		Adolescent-level			
		1 class	2 classes	3 classes	4 classes
1	Single				
	BIC	13643.74	12471.42	12388.647	12390.26
	Entropy	NA	0.721	0.694	0.636
2	Random effects model non-parametric at adolescent-level, parametric at neighbourhood-level				
	BIC		12429.92	12341.007	12319.44
	Entropy		0.723	0.71	0.672
3	Random effects model non-parametric (2 classes at neighbourhood-level)				
	BIC		12486.28	12410.939	12420.01
	Entropy		0.515	0.583	0.594
4	Random effects model non-parametric (3 classes at neighbourhood-level)				
	BIC		12501.12	12433.23	12449.77
	Entropy		0.279	0.609	0.488

Table 13 shows that the latent class 2 is the largest grouping of adolescents (58.7%). It is characterized by adolescents with a low probability of committing acts of aggression. Adolescents in this class 'have made fun of someone' (30%), 'hit with hands' (13%) and 'said hurtful words to someone' (12%). The second largest latent group is class 3 (23.6%). This class is represented by adolescents with the highest probability not only of committing the less serious behaviours –such as 'making fun of someone' (82%), but also of the more severe such as 'hitting with hands' (90%), 'threatening' (60%), 'throwing an object to someone' (38%), 'stealing' (27%) and 'threatening to wound or to kill someone' (6%). The smallest group among the adolescents is class 1 which is represented by adolescents that exhibit a high probability of 'making fun of someone' (73%), 'saying hurtful words' (83%), 'humiliate someone' (49%) and 'throwing an object to someone' (19%). Given the conditional probabilities of each class, label class 1 can be labelled as 'moderate aggressor', class 2 as 'low-aggressor' and class 3 as 'serious aggressor'.

Table 13 Latent class solution for the aggression scale for a three-class model under the non-parametric at adolescent-level parametric at neighbourhood-level approach

Item	Class 1	Class 2	Class 3
	17.7%	58.7%	23.6%
1. Making fun of someone	0.73	0.30	0.82
2. Saying hurtful words	0.83	0.12	0.61
3. Humiliate someone	0.49	0.04	0.42
4. Threatening someone	0.12	0.06	0.60
6. Threatening to wound or kill someone	0.00	0.00	0.06
7. Stealing	0.06	0.02	0.27
8.Defrauding someone	0.02	0.00	0.11
9. Hitting someone with hands	0.09	0.13	0.90
11. Throwing an object to someone	0.19	0.05	0.38
14.Touching somebody's buttocks, legs, breasts or genitals without agreement	0.01	0.00	0.07

The estimated log-odds of the random effect or random mean for the moderate aggressor class is -0.32 (0.35) and its corresponding mean probability 1/(1 + exp(0.32)) = 0.42. The estimated random mean for the low-aggressor class is 1.003 (0.24) and its corresponding mean probability 0.73. This indicates that, for neighbourhoods at the average random mean for both moderate aggressors and low-aggressors, the average probability that an adolescent would be classified as moderate aggressor is around 42% and as a low-aggressor is around 73%. At the neighbourhood-level, the results also confirm the evidence of a substantial heterogeneity of the aggression classes across neighbourhoods. A variance at the neighbourhood level of 1.30 (0.51) is estimated for the moderate aggression class and 0.88 (0.211) for the low-aggressor class. These results indicate that there is variation in the probability of the adolescents to be classified as moderate aggressors or as low-aggressors between neighbourhoods. That is, in some neighbourhoods these probabilities are quite high, whereas in others they are quite low. Finally, the correlation between the moderate aggressor class and the low-aggressor class at the neighbourhood level is 0.79

(0.34), suggesting that neighbourhoods with high levels of moderate aggression also tend to have high levels of low aggression.

Latent class analysis for items defining the delinquency scale

The same procedure is now applied to the items defining delinquency with the results given in Table 14. The single latent class model shows the biggest drop in the BIC when increasing from one to two latent classes (Model 1). Entropy is also high for this solution, indicating that the model is good at distinguishing between adolescents in the two classes. Building on this two-class solution, a parametric approach is fitted to consider the hierarchical structure of the data (Model 2). The BIC declines markedly with the addition of the neighbourhood random effects to the model. Although the entropy declines somewhat in comparison to the single class model, it is still reliable (>0.80), indicating that there is confidence in the separation of the classes. The parametric approach is also estimated with one and three classes. The BIC of the one-class solution shows a substantial improvement from one to two and a slight worsening from two to three. In the final step, this two-class solution is extended to a non-parametric model. The addition of two neighbourhood-level classes does not improve the BIC of the parametric two-class model (Model 3). A third neighbourhood-level class also resulted in a worse fit to the data. Consequently, the two-class solution is chosen as the best model. This model indicates that the delinquency data is well represented by two groups or latent classes at the adolescent level and one continuous random effect at the neighbourhood level.

Table 14 Sequential model comparisons for the delinquency latent trait scale

Model	Specification	Delinquency		
		Adolescent-level		
		1 class	2 classes	3 classes
1	Single			
	BIC	2750.119	2410.579	2418.626
	Entropy	NA	0.926	0.961
2	Random effects model non-parametric at adolescent-level parametric at neighbourhood-level			
	BIC		2379.834	2390.915
	Entropy		0.874	0.878
3	Random effects model non-parametric (2 classes at neighbourhood-level)			
	BIC		2425.442	2440.930
	Entropy		0.608	0.671
4	Random effects model non-parametric (3 classes at neighbourhood-level)			
	BIC		2440.303	2463.218
	Entropy		0.392	0.496

The estimated conditional probabilities of answering 'yes' to each item for each type of delinquents (latent class) are presented in Table 15. In this two-class solution, the largest class is constituted by 92% of the sample. This class shows lower conditional response probabilities than the other class on each of the items and therefore can be named as 'non-delinquents'. This class represents adolescents that rarely have 'hit' or 'threatened to hit someone with an object or a sharp object' or 'having caused a wound'. The second class is formed by the remaining 8% of the sample and is represented by adolescents that are more likely to have 'hit or threatened another person with an object' or to 'cause wounds to someone'. Consequently, this class can be named 'delinquents'.

Table 15 Latent class solution for the delinquency scale for a two-class model under the non-parametric at adolescent-level parametric at neighbourhood-level approach

Item	Class 1	Class 2
	0.08%	91.7%
5. Threatening to hit someone with an object	0.675	0.022
10. Hitting another person with an object	0.766	0.038
12. Attacking someone with a sharp object	0.122	0.004
13. Wounding someone	0.170	0.004

The estimated log-odds of the random mean for the delinquent class is -2.81 (0.26) and the corresponding mean probability is 1/(1 + exp(2.81)) = 5.68%. This indicates that, for neighbourhoods at the average random mean for delinquency, the average probability that an adolescent would be classified as a delinquent is around 6%. The variance of this random mean is also statistically significant 1.62 (0.44), indicating that there is variation in the probability of the adolescents belonging to the delinquent class between neighbourhoods. That is, in some neighbourhoods the probability is quite high, whereas in others it is quite low.

The map of the estimated means of the random effects for each of the aggression and delinquency classes (Figure 24) shows results that are very consistent with those obtained from the Rasch multilevel model, in particular for the delinquency random mean. Neighbourhoods with high mean for the moderate aggressor class are located in the east part of the city, while those with the highest low aggression class are in the north. For the delinquency classes, most of the neighbourhoods on the north side of the city fell within the highest tercile.

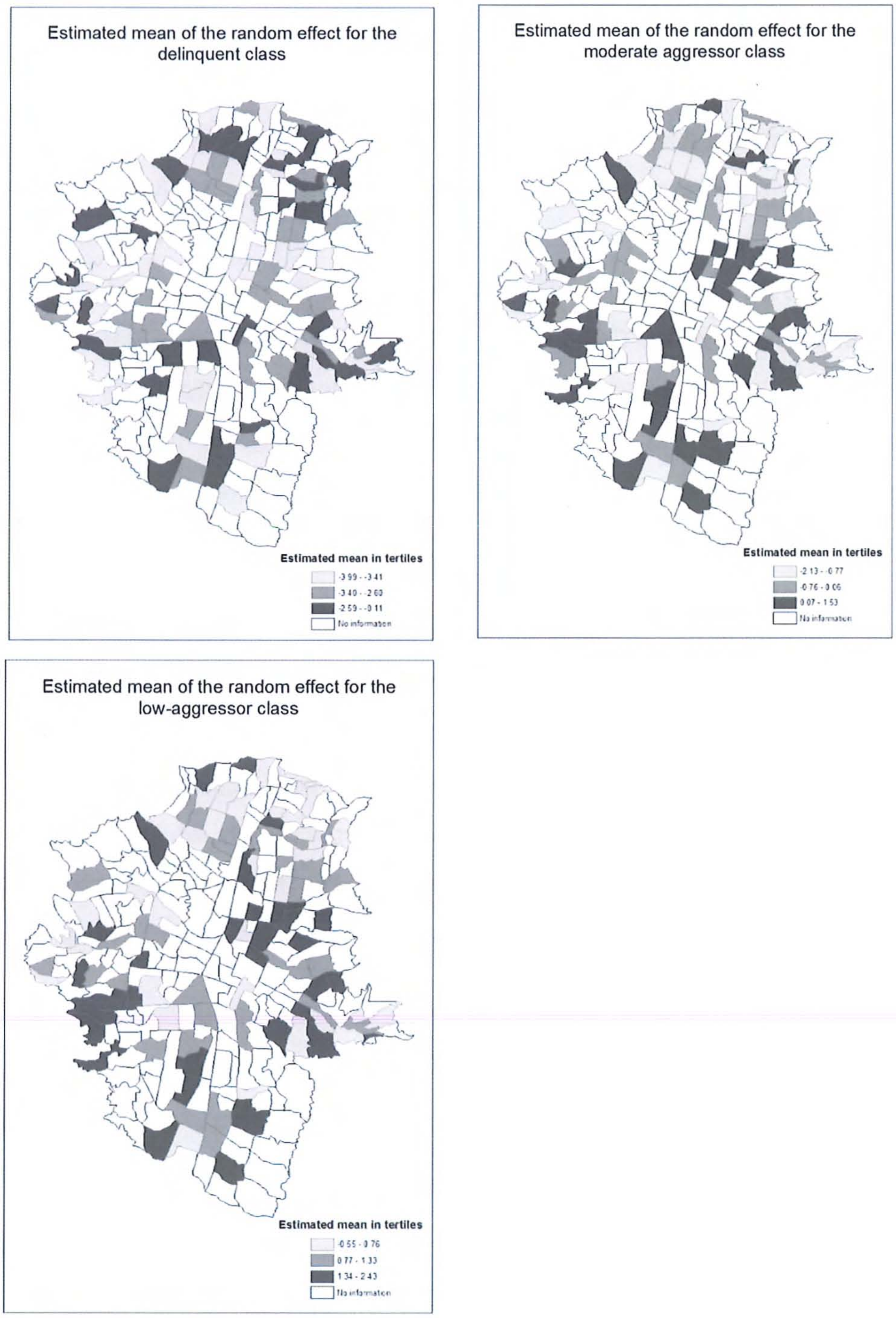


Figure 24 Estimated mean of the random effects for the aggression and delinquency classes in terciles. Medellin, 2007

Conclusions

The main concern in this chapter is to measure individual and neighbourhood latent traits of adolescent aggressive behaviour and to assess their psychometric properties by using Item Response Theory models and a variety of different forms of hierarchical modelling.

After controlling for measurement error, results from the three-level Normal-theory Rasch model show that aggressive behaviour in Medellin has marked neighbourhood differences. There is significant variation of both aggressive behaviour scales at the neighbourhood and individual-level. Some 7% of the aggression and 14% of the delinquency variation is at the neighbourhood level. The MOR statistic permits a more natural interpretation in terms of odds ratios confirming the presence of large variation between neighbourhoods in the propensity of the two aggressive behaviours; these differences are greater for delinquency.

The multilevel Rasch procedure permits an assessment of reliability at the level of the adolescent and the neighbourhood. The reliability indices indicate that it is possible to reliably measure aggressive behaviour at both individual and neighbourhood levels. For the aggression scale, the values at the adolescent-level are 0.71 and at the neighbourhood-level 0.94. These values indicate that the calculated log-odds of aggression is a reasonable estimate for the true individual/neighbourhood scores. However, for the delinquency scale, the reliability measures at individual and neighbourhood level are significantly lower than the aggression scale, with values of 0.21 and 0.19 respectively, indicating that discriminating between delinquent individuals is less reliable in this sample. The spatial multiple membership model did not find a significant effect for adjoining areas in addition to the specific neighbourhood in which the adolescent lives. This indicates that the level of aggression and delinquency is independent of the level of aggressive behaviour in adjacent neighbourhoods with data, and that the responses from the own neighbourhood where the adolescents live are more important in determining the level of individual and neighbourhood aggressive behaviour than the responses from neighbouring areas.

A substantial finding of the multilevel Rasch estimation is the distribution of the estimated latent scores of the adolescents. The distribution of the individual residuals for both aggressive behaviour scales is positively skewed, indicating that the Normality assumption of the one-parameter Rasch model may not hold for the Medellin population. Applying the multilevel latent-class methodology to the aggression scale items, three groups of adolescents are identified: moderate aggressors (18%), low-aggressors (59%) and serious-aggressors (24%). Similarly, rather than a continuous trait of delinquency, the the presence of two meaningful groups of delinquents at adolescent-level is revealed: 8% classified as delinquents and the remaining 92% as non-delinquent. In this multilevel latent class analysis, the parametric approach provided the best fit to the data, indicating the presence of three continuous neighbourhood latent variables: low and moderate neighbourhood aggression and neighbourhood delinquency. Comparing the geographical distribution of the estimated neighbourhood latent traits of aggressive behaviour obtained from the multilevel Rasch model with the estimated means of the random effects obtained from the multilevel latent class model, a very similar pattern is observed. Neighbourhoods located at the north side of the city have a higher probability of being classified as delinquents, while the east part is characterised by moderate/low aggressors.

This chapter and the last has used a variety of multilevel modelling techniques to create uni-dimensional scales that reliably and validly measure latent traits of aggressive behaviour for adolescents and neighbourhoods while adjusting for measurement error. These scales both continuous and categorical, will serve in subsequent analyses as the response variables. That is, the current Normal theory measurement model, as well as the multilevel latent class model, will be extended to include relevant predictors at the individual and neighbourhood level that help to explain the variation at both levels.

Chapter 5. Measuring neighbourhood characteristics

While Chapter Four is concerned with measuring aggressive behaviour for individuals and neighbourhoods, this chapter aims to create a range of variables that measure neighbourhood conditions. These derived variables are then used to understand the underlying processes of neighbourhood effects on aggressive behaviour. The construction of these variables is based on official government datasets and also on two independent community surveys of households living in the same neighbourhoods as the adolescents under study. To derive valid measures, five analytical procedures are used according to the nature of the data being analysed: multilevel factor analysis, ecometrics, spatial multiple membership models, Geographic Information Systems and hierarchical Bayes procedures. The result is nine neighbourhood variables which cover the two distinct neighbourhood characteristics highlighted in Chapter Two: structural and social conditions. These variables are used in the next chapter as neighbourhood predictors to evaluate various substantive hypotheses about aggressive behaviour.

This chapter is organized in six main sections. First, the most common approaches to measuring neighbourhood conditions are outlined. The second and third sections are concerned with the measurement of structural and social neighbourhood conditions using survey data. These sections combine the use of latent variable models, ecometrics and spatial multilevel models to derive valid and reliable neighbourhood constructs. The fourth and fifth sections focus on the measurement of accessibility to neighbourhood resources and neighbourhood homicide using data derived from administrative datasets. These sections describe the use of Geographic Information Systems (GIS) and spatial statistics to derive a set of neighbourhood variables. Finally, the chapter ends with a brief conclusion that looks at the correlation between these different elements of neighbourhood characteristics.

Approaches to measuring neighbourhood constructs

A variety of sources and approaches are used to measure neighbourhood conditions. The most widely utilized source of data is census or local administrative data sets that cover a full range of conditions such as health, human service, education and public safety. The second most common source of data is community surveys. In general, these surveys are designed to characterize and monitor household living conditions and to elicit individual perceptions about social processes in their neighbourhood, such as disorder, crime, and trust among neighbours (McWayne et al., 2007, Rajaratnam et al., 2006).

From a detailed reading of the literature, neither administrative data nor survey data alone offers a complete picture of the neighbourhood conditions and, consequently, the triangulation of all available neighbourhood-level data is strongly encouraged in research that addresses complex problems such as aggressive behaviour (Sampson et al., 2002b, Leventhal and Brooks-Gunn, 2000). In addition, researchers have highlighted the need to use statistical methods to derive neighbourhood constructs that precisely represent the different facets of neighbourhood environments, rather than reflecting the individual conditions of their household population (Sampson et al., 2002a, Cummins et al., 2005). In line with this, neighbourhood researchers have developed a wide range of theoretically-grounded approaches to measuring aspects of physical and social neighbourhood conditions that could buffer or exacerbate neighbourhood effects (Kawachi and Subramanian, 2007). Depending on the nature of the available data, which can be counts, aggregate data or household data, novel applications of statistical methods, as well as GIS techniques have been developed to build and to establish the validity and reliability of these derived ecological measures.

Converting administrative data into neighbourhood measures is relatively straightforward. In practice, these one is generally available as summaries for geographical units which can be used either as frequencies or proportions. Another strategy used to transform this administrative data is the application of GIS technology and spatial statistics which is used to estimate smoothed area-level indicators, such as rates of prevalence of the events of interest. Regarding survey data, the most common strategy used by researchers is simple aggregation of the data using existing geographical units and the calculation of indicators such frequencies and proportions.

Standard factor analysis is the technique commonly employed by researchers to reduce the number of neighbourhood indicators, to avoid multicollinearity and to estimate uni-dimensional neighbourhood scores (Rajaratnam et al., 2006). Although this technique potentially provides a rich summary of the underlying structure of the data and the correlation between the neighbourhood indicators, it makes unrealistic assumptions. For example, it is typically assumed that the set of 'input' variables are all measured on a set of independent units (when using survey data), or that the resultant neighbourhood latent variables are continuous with a known distribution. These assumptions may be problematic when, for example, the input variables are obtained through a complex multistage sample design or when the higher-level latent constructs are discrete rather than Normal (Vermunt et al., 2004). Failure to consider the real nature of the data, its variation at the household and neighbourhood level and its most appropriate distributional shape can produce misleading results that may affect the subsequent analysis of neighbourhood effects (Toland and De Ayala, 2005).

Moreover, when using survey data to generate neighbourhood-level constructs, there is the potential of committing an atomistic fallacy, that is incorrectly assuming that the relationship between variables observed at the household-level holds for the neighbourhood-level versions of the variables (Robinson, 2009). Empirical evidence to date suggest the existence of three different neighbourhood-level variables that may emerge from survey data: the first refers to neighbourhood-level variables that only operate at neighbourhood-level, so the resultant variables only have a conceptual meaning at the neighbourhood-level; for example, social cohesion or collective efficacy. The second corresponds to neighbourhood-level constructs that are meaningful at both household and neighbourhood-level; for example, poverty or deprivation. Finally, the third corresponds to neighbourhood-level variables that operate at multiple levels but with a different factor structure at different levels of analysis (Chan, 1998). It has also been found that the number of factors at the neighbourhood-level tend to be smaller than the number of factors at the household-level (Muthén, 1994). Consequently, ascertaining the emergent properties of neighbourhoods and their potentially separate structure is a critical issue to ensure that the resultant constructs are uni-dimensional and have good construct validity properties at that level of analysis.

Recent methodological developments (Goldstein et al., 2008, Muthén, 1994) address these problematic issues with the standard Normal theory single-level factor analysis. These techniques are called multilevel factor analysis and multilevel latent class analysis. Both approaches may be used to analyze any combination of categorical and continuous variables which are derived from hierarchical data with households nested in neighbourhoods. Both procedures allow separate factor structures at household and neighbourhood-level (Goldstein and Browne, 2002, Vermunt, 2003b). The main difference between the two is based on the nature of the latent variables that are estimated. While multilevel factor analysis creates continuous latent trait variables at household and neighbourhood-level, the multilevel latent class analysis, as described in Chapter Four, creates a number of latent classes at household-level and either classes or latent traits at the neighbourhood-level.

These procedures have only recently been introduced, and an extensive literature search found only three studies employing multilevel factor analysis and one employing multilevel latent class analysis for measuring underlying neighbourhood dimensions. Doebler (2009) uses multilevel factor analysis on 12 USA Census-block measures to create three structural neighbourhood constructs: Neighbourhood Deprivation, Concentrated Disadvantage, and Townsend Material Deprivation at the census tract and neighbourhood-levels. Similarly, Cerda *et al.* (2008) use multilevel confirmatory factor models to combine a set of ordinal responses derived from a community survey in Medellin, Colombia to create continuous measures of collective efficacy and perceptions of neighbourhood violence, scales that are subsequently used as response variables in the analysis.[3] Brown *et al. (2008)* also analyzed a nine-item questionnaire, from 599 community leaders nested in 41 communities, to measure the construct of prevention collaboration at both individual level and community-level. In the final study, Tobler *et al.* (2009) combined census data with survey data from 4,215 youths residing in 42 community areas in Chicago, and identified five classes of social capital and exposure to alcohol.

Quality, reliability and validity are controversial issues when developing neighbourhood constructs using survey data. As argued by Mujahid and colleagues (2007), reports made by neighbourhood households are not only influenced by their objective reality, but also by 'personal factors and perceptions which may introduce measurement error' (Mujahid et al., 2007, p 859). As a response to this, Raudenbush and Sampson (1999b) developed a method that allows the assessment of the quality of neighbourhood domains derived from survey data in terms of internal consistency and reliability. This method is named *ecometrics,* an approach that incorporates and adapts psychometric tools and applies them in an ecological setting. This involves generalizability theory, item response theory and multilevel modelling to properly identify sources of error and to adjust for the subjective assessment of the household response (Raudenbush and Sampson, 1999b, Gauvin et al., 2005). This method is increasingly being applied by neighbourhood researchers (Fone et al., 2006, Gauvin et al., 2005, Mujahid et al., 2007, Poortinga et al., 2007, Echeverria et al., 2004) who derive theoretically rich and empirically meaningful constructs of mainly social neighbourhood conditions, which are subsequently

[3] Unfortunately, the detailed factor scores are not available for comparison with the present study.

used as predictors in analyses relating neighbourhood characteristics to a variety of different individual-level outcomes.

Thus, this chapter uses a combination of statistical analyses in a novel approach to create neighbourhood constructs. The novelty is a six-step procedure (described in detail below) that uses the multilevel factor analysis to identify relevant variables and constructs at the level of interest (neighbourhood), and then uses the identified variables that make up the neighbourhood construct in an ecometric model to evaluate its properties in terms of reliability and inter-rater agreement. This ecometric model is specified as a spatial multiple membership model to evaluate the spatial dependency of the resultant neighbourhood scores and to improve the model estimates. It also uses latent class modelling in those cases when the neighbourhood-latent variables are found to be better represented by categorical constructs rather than continuous constructs.

This combination of approaches has not been previously used in the measurement of neighbourhood constructs. The result is a set of uni-dimensional scales of neighbourhood variables that have known properties of reliability and validity. Moreover, the multilevel nature of the analysis separates out the neighbourhood and household component of the variation, while the random effects nature of the models results in precision-weighted estimation of the scores for each neighbourhood (Shin and Raudenbush, 2010, Bullen et al., 1997).

Measuring structural neighbourhoods characteristics

As discussed in Chapter Two, structural characteristics refer to the socioeconomic condition of the neighbourhoods and the physical conditions of public areas (Mrug and Windle, 2009, Rajaratnam et al., 2006). In general, research exploring neighbourhood effects on adolescent development has analysed three main neighbourhood dimensions: concentrated disadvantage, neighbourhood deprivation and residential instability. Concentrated disadvantage is an indicator of relative poverty. It reflects the concept of concentration of residents in areas with high levels of poverty, higher proportion of families headed by single females, unemployment and low living standards (Sampson et al., 1997). Deprivation refers to problems caused by a lack of resources and opportunities in different human necessities, such as income, employment, education, housing, access to services, health, community safety and physical environment (Doebler, 2009). Residential instability is a measure of the residential turn-over, or mobility, within a neighbourhood. Most commonly, this dimension is measured using the proportion of households who moved within the past five years and the proportion of residents who own their home (Boggess and Hipp, 2010, Drukker et al., 2005).

For this study, the available data to create the structural neighbourhood conditions are derived from a community survey 'The Life Quality Survey of Medellin', conducted in 2007. The final sample corresponds to 20,409 households who provide data on 244 neighbourhoods of the city. Given the hierarchical structure of the data, where households are nested within neighbourhoods, and the specific interest in creating variables operating at the neighbourhood-level, multilevel factor analysis stands as the most appropriate approach to explore this data. The nature of the data is first considered and then the proposed analytical strategy to integrate the multilevel latent methods is detailed.

The Life Quality Survey

The aim of the Life Quality Survey of Medellin is to provide information about the size and structure of the city population at two different levels: individual and household. The survey used a stratified sample design where households were randomly selected within each *comuna* in a way that would include them in each of six different social class stratums and with representation of all neighbourhoods of the city (Medina et al., 2008). For each household, the head of the household (defined as a habitual resident of the house, recognized as head by the other members of the household) and members aged 18 and older were interviewed, representing a final sample of 75,280 respondents belonging to 20,413 households from 244 neighbourhoods. To estimate the structural neighbourhood constructs, the data provided by the head of the household are used. Only four respondents are removed from the data set, given that their neighbourhoods are wrongly coded.

Based on the literature, the following set of variables are selected: gender of the head of household (female, male); health security system to which the household is affiliated (contributive, subsidized, beneficiary, special regimen, not affiliated, other); highest level of education achieved (none, primary, high school, undergraduate, master, PhD); type of house ownership (rented, own already paid, own being paid, borrowed, squat and other) and number of years living in the neighbourhood (continuous). Data from the family members are also aggregated to obtain household measures for economic activity in the last week (working, looking for a job, studying, housekeeper, private income, retired, disabled, other) and the highest level of education achieved.

Using these individual responses, seven household indicators are derived and recoded, so that higher values consistently indicate a higher status. Table 16 shows the distribution of these indicators. The average age of the heads of households is 50.6 years old; 39.4% are females, a third of them had studied to a maximum of primary school. More than fifty percent of the families do not have a member with a professional qualification, and in around one tenth of the families there is someone unemployed. The average percentage of people who live in rented accommodation is 35% and around one third of the families have lived in the neighbourhood for less than five years. The survey is judged to be a highly representative one.

Table 16 Individual characteristics of the head-households residing in neighbourhoods of Medellin, 2007

Variable	N	%
Female head-house		
Yes	8,044	39.4
No	12,365	60.6
Head-house on health public assistance		
Yes	4,577	22.4
No	15,832	77.6
Head-house with Primary education or less		
Yes	7,555	37.0
No	12,854	63.0
No family members with a professional qualification		
Yes	11,788	57.8
No	8,621	42.2
One or more family members is unemployed		
Yes	1,576	7.7
No	18,833	92.3
Rented house		
Yes	7,166	35.1
No	13,243	64.9
Less than 5 years living in the neighbourhood		
Yes	4,155	31.9
No	8,853	68.1

The multilevel factor model for binary items

Multilevel factor analysis is an extension of the standard factor analysis model which aims to reduce the dimensionality of a number of variables and to create 'common factors' that capture the majority of the variation in the data at both individual and neighbourhood level (Browne, 2003, Hox, 2002, Goldstein and Browne, 2002, Dedrick and Greenbaum, 2010).

Multilevel exploratory factor analysis and multilevel confirmatory factor analysis are the two approaches that are required to be used in combination. The former refers to an inductive approach used to explore the dimensionality of the variables by finding the smallest number of interpretable factors at each level of analysis, without imposing any restriction on the parameter estimates. In contrast, the latter approach, imposes restrictions on the model parameters based on the results of the exploratory analysis or on previous theory (Skrondal and Hesketh, 2007). A particular strength of both approaches is that they allow evaluation of a variety of models including those that have the same number of factors at each level and those that have a different number at each level.

In the current analysis, these models have a three–level structure: items at level-1, households at level-2 and neighbourhoods at level-3 with random effects at level-2 and level-3, and level-1 variance constrained by the assumption of Binomial variation (Goldstein and Browne, 2005). A three-level factor model with binary items can be specified (Steele and Goldstein, 2006) as:

$$Probit(y_{ijk}) = \beta_0 + \lambda_i^{(2)}\eta_{jk}^{(2)} + \cdots + \lambda_i^{(3)}\eta_k^{(3)} + u_{ijk} + v_{ik}$$

$$\eta_{jk}^{(2)} \sim N(0, \Omega_{v(2)}),\ \eta_{jk}^{(3)} \sim N(0, \Omega_{v(3)}), u_{ijk} \sim N(0, \sigma_{ijk}^2), v_{ik} \sim N(0, \sigma_{ik}^2)$$

In this model, y_{ijk} is the response on variable *i* for household *j* in neighbourhood *k*; β_0 is the overall intercept, $\lambda_r^{(2)}$and $\lambda_r^{(3)}$are the level-2 and level-3 factor loading parameters. The latent factor scores or latent trait values for each household and neighbourhood are described by $\eta_{jk}^{(1)}$ and $\eta_j^{(2)}$ which are assumed to be Normally distributed with variance at level-2 and level-3 denoted by $\Omega_{v(2)}$ and $\Omega_{v(3)}$ which are constrained to 1 to make the model estimable. When two or more factors are specified at a particular level, it is possible to estimate their correlation. Finally, u_{ijk} and v_{ik} represent the residual random household and neighbourhood effects, referred to as 'uniqueness', or the specific factors that correspond to each response *i*. These terms are mutually independent and are assumed to have Normal distribution with variance σ_{ijk}^2 and σ_{ik}^2 (Steele and Goldstein, 2006). The model uses the Probit link of the underlying probability of the latent construct. The use of this Probit model facilitates estimation by MCMC procedures as it much easier to implement than the equivalent logit, but gives very comparable results (Browne, 2009, Chapter 10).

This specification of the three-level factor model has close parallels with the specification of the two-parameter IRT model described in Chapter Three. That is, under the formulation of the multilevel factor model, the overall intercept corresponds to the 'item difficulty' within the standard formulation of the two-parameter model, and the factor loadings for each variable correspond to the 'item discrimination' parameters (Raudenbush and Sampson, 1999b). The difference between the two models resides in the fact that multilevel factor analysis allows the specification of more than one potentially correlated latent factor, while the two-parameter model can estimate only one factor at time.

The ecometric model for binary items

Following Raudenbush and Sampson (1999b), the ecometric method uses a three-level item response model (items at level-1, households at level-2 and neighbourhoods at level-3) to estimate two reliability coefficients, known as the ecometric properties of the neighbourhood dimensions: i) inter-rater agreement which measures the validity of the scale by assessing the level of agreement in the household perceptions of their neighbourhood, and ii) the reliability of measurement at the neighbourhood-level, which indicates whether the estimated trait is a reasonable estimate for the true neighbourhood score (Raudenbush and Sampson, 1999b, Diez-Roux, 2007).

The specification of the ecometric model follows the same model structure of the three-level Rasch model applied in Chapter Four, where the factor loadings (i.e. discrimination parameters) are effectively constrained to be equal to one, while the latent trait variances are allowed to vary (Raudenbush and Sampson, 1999b). In addition, the ecometric model can include individual covariates at household-level to control for the subjective assessment of the neighbourhood constructs and thus to reduce the magnitude of subjective bias in the data. Consequently, the ecometric model includes household-level covariates that are known to increase or decrease the subjective rating of the neighbourhood as positive or negative: age, gender, social class, home ownership and living in the same neighbourhood for less than 5 years.[4]

The ecometric model with the additional household-level covariates is defined as:

$$y_{ijk} \sim Binomial \quad (Cons_{ijk}, \pi_{ijk})$$

$$\log e\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \beta_0 x_{0ij} + \beta_1 x_{1ijk} + \ldots + \beta_{i+1} x_{i+1jk} + u_{0jk} x_{0ij} + v_{0k} x_{0ijk};$$

$$u_{0jk} \sim N(0, \sigma^2_{u0}); v_{0k} \sim N(0, \sigma^2_{v0}); \qquad Var(y_{ijk} \mid \pi_{ijk}) = \sigma^2_e \pi_{ijk}(1-\pi_{ijk})$$

where y_{ijk} is a set of binary household responses for question *i* as reported by household *j* in neighbourhood *k*. Cons is the number of trials of the Binomial distribution, here a set of 1, and π_{ijk} is the estimated probability of saying 'yes' to question *i* for household *j* in neighbourhood *k*. The x_{ijk} terms are a series of dummy variables representing the *i*-1 items in the neighbourhood scale as reported for household *j* in neighbourhood *k*. These indicator variables are centred around their grand mean (1/*n*, *n* being the total number of items in the scale). This specification allows β_0 to be interpreted as the log-odds of a *typical* household on his/her latent trait score responding affirmatively to a typical neighbourhood question in the typical neighbourhood. Controls for the subjective assessment of the neighbourhood conditions are represented byX_{jk}, which corresponds to the individual covariates at the household-level. There are two higher-level random terms: u_{0jk} , which is the latent trait of the neighbourhood scale for household *j* in neighbourhood *k*, and v_{0k}, which is the underlying propensity for the neighbourhood on the logit scale. The household latent traits are summarised by the varianceσ^2_{u0}, while the neighbourhood

[4] In practice, households are also individuals and the covariates either relate to the head of the household or the entire household as appropriate.

differentials are summarised by σ^2_{v0}. The level-1 variation represents the variation in the observed binary outcome y_{ijk}, given the estimated probability of saying 'yes' (π_{ijk}). This is determined by σ^2_e, which is constrained to 1 as it is a Bernoulli distribution.

This model formulation calculates a precision-weighted estimate, which indicates that in neighbourhoods with small number of households, the resultant neighbourhood latent trait is shrunk back towards the average city overall mean. [5] As explained in Chapter Four, a spatial multiple membership model can improve such estimates by 'pooling' information over surrounding neighbourhoods. Therefore, the resultant estimate is shrunk towards the grand mean of the neighbouring neighbourhoods rather than the grand mean across all the city neighbourhoods (Browne, 2003). As described in Chapter Four, this is achieved by specifying an ecometric spatial multiple membership model that separately estimates: 1) between household effects, 2) aspatial between neighbourhoods effects, and, 3) spatial neighbouring effects. The specification of this model follows that of Chapter Four, but now includes household-level covariates to control for potential measurement bias.

A six fold schema to develop neighbourhood variables

The specification, identification, estimation and interpretation of multilevel latent models, follows the analytical strategy of Muthén (1994) which is further extended by the present researcher to include the ecometric model. Muthén's strategy consists of a four-stage process that starts with simpler models before conducting a complete multilevel factor analysis. After this, two additional stages are included in the analysis that assesses the ecometric properties of the

[5] The mean number of observed households in a neighbourhood is 84, the minimum 3 and the maximum is 295. The formula for shrinkage in a three-level model is given by Raudenbush and Bryk (2002, 251). This shows that the neighbourhood differential will be shrunk towards household level which will be shrunk towards the grand mean across all neighbourhood households and items; the degree of shrinkage depending on the size of the variance and the number of units, with greatest shrinkage where there is little information and the where the raw residual would be imprecisely estimated.

neighbourhood scores, their spatial dependency, their distributional assumptions, and if necessary, identifies neighbourhood latent classes. The complete scheme is described as a flow diagram in Figure 25:

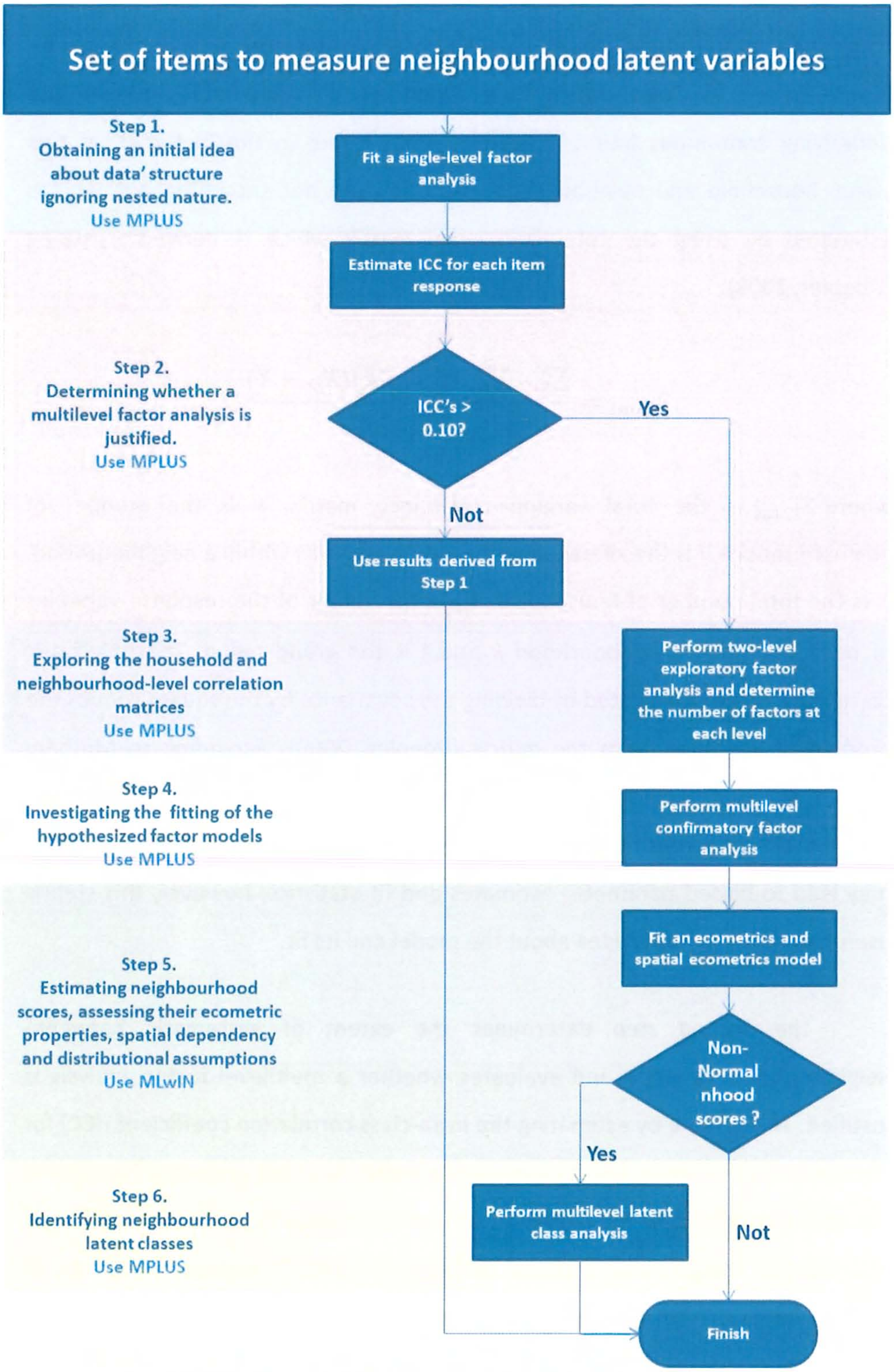


Figure 25 Flow diagram to create neighbourhood-level constructs using survey data

The *first step* recommended by Muthén consists in obtaining an initial idea about the structure of the data ignoring its nested nature. This is done by conducting a single-level exploratory factor analysis on the total polychoric correlation matrix. A polychoric correlation is required because of the binary nature of the variables, which then estimates the correlation between the underlying continuous latent indicators. Total refers to the fact that, at this stage, household and neighbourhood variation are not separated out. This is estimated by using the total covariance matrix which is derived by using (Doebler, 2009):

$$S_{Total} = \frac{\sum_{k=1}^{K}\sum_{j=1}^{J_k}(X_{jk} - \bar{X})(X_{jk} - \bar{X})}{(N-1)}$$

where S_{Total} is the total variance-covariance matrix, *k* is the number of neighbourhoods, *j* is the average number of households within a neighbourhood, *N* is the total number of households, X_{jk} is the vector of the response variables of households *j* in neighbourhood *k* and $\bar{X}$ is the grand mean. The polychoric correlation is then calculated by dividing the covariance by the square root of the product of variances from the matrix (Doebler, 2009). According to Muthén, when there is considerable non-independence in the responses or when the factor structure across the hierarchical levels is different, this single-level model may lead to biased parameter estimates and fit statistics; however, this step is useful to obtain an initial idea about the model and its fit.

The *second step* determines the extent of systematic between-neighbourhood variation and evaluates whether a multilevel factor analysis is justified. This is done by estimating the intra-class correlation coefficient (ICC) for each response variable. The ICC provides a measure of the amount of variability between households or the degree of non-independence in the responses. This is estimated by using a random effects model, where the ICC is given by the ratio of the estimates of the variance at the household-level and the variance at the neighbourhood-level. Thus, it can be expressed as:

$$ICC = \sigma_{ik}^2/(\sigma_{ik}^2 + \sigma_{ijk}^2)$$

ICC values greater than 0.10 indicate that there is enough variability in the responses across neighbourhoods to justify multilevel modelling techniques (Dyer et al., 2005, Dedrick and Greenbaum, 2010).

The *third step* separates the total variance-covariance matrix into household-level variance-covariance matrix (S_{Within}) and neighbourhood-level variance-covariance matrix ($S_{Between}$), and performs exploratory factor analysis on their corresponding polychoric correlation matrices. The household-level variance-covariance matrix provides unbiased estimators of the household-level parameters which are adjusted to remove neighbourhood-level differences. This is done by subtracting the relevant neighbourhood means ($\bar{X}_k$) from household scores, as shown below (Doebler, 2009):

$$S_{Within} = \frac{\sum_{k=1}^{K}\sum_{j=1}^{Jk}(X_{jk} - \bar{X}_k)(X_{jk} - \bar{X}_k)}{(N-1)}$$

The values of the neighbourhood-level variance-covariance matrix are the observed neighbourhood means corrected for the grand mean ($\bar{X}$). This variance-covariance matrix is estimated by (Doebler, 2009):

$$S_{Between} = \frac{\sum_{k=1}^{K} J_k(\bar{X}_k - \bar{X})(X_k - \bar{X})}{(K-1)}$$

The exploratory factor analysis is performed simultaneously on the corresponding household and neighbourhood-level correlation matrices, which are calculated by dividing each variance-covariance matrix by the square root of the product of variances from each matrix (Doebler, 2009). This two-level exploratory factor analysis provides not only an indication of the factor structure at each level but also a better understanding of the number of factors needed (which may be different at each level), the quality of the measurement instruments, the variables that are poor factor indicators (variables with low loadings) and the factors that are poorly measured (factors with less than two variable indicators). In practice, the factor analysis literature does not recommend a specific cut-off value to determine whether a variable is a substantive indicator. However, the suggested cut-offs values made by Comrey and Lee (1992) seems to be appropriate and are used here: factor loadings >0.71 are excellent, >0.63 are very good, >0.55 are good, >0.32 are fair, and <0.30 are poor.

An important decision that needs to be made in this exploratory step is to determine the appropriate number of factors at each level. There are a number of goodness of fit statistics to guide that decision (Yu, 2002): chi-square goodness-of-fit statistic, Standardized Root Mean Square Residual (SRMR) and Root Mean Square Error of Approximation (RMSEA).[6] Researchers recommend evaluating all these indicators, because each has limitations and there is no single preferred method in the multilevel factor analysis literature (Dedrick and Greenbaum, 2010). A good model is expected to have a non-significant chi-square value (>0.05); however, this is an unstable statistic, sensitive to neighbourhood sample size and to the clustering effect of the responses (ICC). When using large samples and when the values of the ICC are large, the chi-square gives statistically significant results, even though the model is substantially correct. Therefore, this indicator is not used in this study to evaluate fit. Alternatively, researchers base their model assessment on SRMR and RMSEA which give an acceptable test when values are lower than 0.08 (Hu and Bentler, 1999). The best model meeting most, if not all, the goodness-of-fit statistics is said to account for most of the correlations among the observed variables.

The *fourth step* of the Muthén strategy uses the outcomes of the two-level exploratory factor analysis to perform multilevel confirmatory factor analysis. This step makes use of the household-level variance-covariance (S_{within}) and the neighbourhood-level variance-covariance ($S_{Between}$) matrices

[6] Detailed formulae are given in Yu (2002)

simultaneously to investigate how well the hypothesized factor models fit the sample. This is done by using constraints on factor loadings, variances, covariances and residual variances. The assessment of the goodness-of-fit of the final model can be done not only by using SRMR and the RMSEA indicators, but also the Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI). These indices are also chi-square comparisons of the target model to a baseline model, and are expected to have values higher than 0.95 (Hu and Bentler, 1999).

Once the Muthén steps have been followed, there is good knowledge about the factor structure that represents the data at neighbourhood level, and thus, it is reasonable to estimate the underlying neighbourhood constructs. However, the aim in this chapter is also to measure the ecometric properties of these neighbourhood constructs and to evaluate the model assumptions of the random terms. Therefore, the Muthén strategy is extended by adding another two steps.

The *fifth step* of the analysis involves setting up the ecometric model to estimate the neighbourhood scores, to assess their ecometric properties, to evaluate their spatial dependency and to evaluate their distributional assumptions. The variables that constitute distinctive uni-dimensional neighbourhood constructs are used in this step to fit separate ecometric models. The resultant covariance matrices are used to assess the two ecometric properties of the neighbourhood dimensions:

1. The inter-rater agreement, which is measured by the intra-neighbourhood correlation coefficient (ICC) described in Chapter Four. Its values range from 0 to 1 where higher values indicate greater agreement between households within a neighbourhood (Mujahid et al., 2007).
2. The reliability at the neighbourhood-level is estimated by using the formula also described in Chapter Four. This measure ranges from 0 to 1, with higher values indicating high sensitivity of the ecometric model to distinguish between neighbourhood differences in the scores of the

neighbourhood constructs. Following Mujahid *et al.* (2007), reliability coefficients > 0.8 can be interpreted as excellent reliabilities, 0.7 to 0.8 as very good, 0.6 to 0.7 as satisfactory, and <0.6 as problematic.

Once the ecometric properties of the neighbourhood scales have been established, the spatial dependency of the resultant scores are evaluated by a spatial multiple membership model. In the manner of Chapter Four, the Deviance information criterion (DIC) is used to compare the fitting of the ecometric model without spatial effects and the one that includes additional spatial effects. The model with the smaller DIC is deemed as the better to estimate the final latent neighbourhood scores (Browne, 2003).

The chosen model is then used to evaluate the distributional assumptions of the neighbourhood random effects. This is done by using a histogram of the estimated neighbourhood latent scores. An approximated Normal distribution would indicate that the final latent trait variable is an acceptable specification for the data. Conversely, concerns about non-Normality or groups may reveal that a latent binary or ordered variable better characterised the neighbourhood construct. If this is the case, it would be necessary to proceed to the next and final step.

The *sixth step* of the analysis identifies neighbourhood latent classes using the non-parametric approach of multilevel latent class analysis. This is accomplished in the same manner as in Chapter Four with the four-step procedure of *Lukociene and Varriale* (2010) and *Henry and Muthén* (2010) being deployed to determine the number of neighbourhood latent classes.

The multilevel factor model and latent class model are estimated using MPLUS Version 6.11 software (Muthén and Muthén, 1998-2010), and the ecometric models are calibrated using MLwiN 2.22 software with MCMC estimation.

Results

Step 1. Performing single-level exploratory factor analysis.

Based on the total polychoric correlation matrix, a single exploratory factor analysis is undertaken using Varimax rotation, a rotation that provides solutions with uncorrelated factors. The number of factor solutions to be explored with the data is specified in Mplus, and this is done by examining solutions up to a maximum of three factors. The corresponding goodness of fit statistics are shown in Table 17. A solution with three factors does not produce estimates, while the remaining results suggest the presence of two factors. The measures of fit suggest that the fit is acceptable. The SRMR of 0.04 and the RMSEA of 0.05 are within the cut-off values suggested by *Hu and Bentler* (1999).

Table 17 Model fit for a single-level exploratory factor analysis of structural conditions

Factors	RMSEA	SRMR
1	0.05	0.07
2	0.05	0.04
3	-	-

This preferred two factor solution is shown in Table 18. Factor loadings with asterisks represent loadings significant at the 5% level, where bold loadings are the more substantive indicators with factor loadings ≥0.30. For Factor 1, the factor loadings indicate the presence of a disadvantage factor with substantive loadings on the following variables: *'Female head of house', 'head of the household receiving public health benefits', 'Head-house with Primary education' or less'* and *'No family members with a Professional qualification'*. For factor 2, the most important variables are *'Rented house'* and *'Less than 5 years living in the neighbourhood'*. These results strongly indicate the presence of two different constructs, one measuring what in structural neighbourhood terms is called 'disadvantage' and the other measuring 'residential instability'.

Table 18 Standardized factor loading from a single-level exploratory factor analysis of structural conditions

	Loadings		
Variables	**Factor 1**	**Factor 2**	**ICC**
Female head-house	**0.30***	-0.02	0.01
Head-house on health public assistance	**0.59***	0.09*	0.34
Head-house with Primary education or less	**0.48***	-0.10*	0.18
None family members with a Professional qualification	**0.55***	-0.07*	0.18
One or more family members is unemployed	0.24*	-0.01	0.07
Rented house	0.05*	**0.60***	0.05
Less than 5 years living in the neighbourhood	-0.14*	**0.44***	0.28

Step 2. Estimating the intra-class correlation coefficient (ICC) for each response variable

The intra-class correlations (ICCs) for each of the seven variables are computed by estimating a three-level model. The last column of Table 18 displays the ICCs for the seven variables. The ICCs values items range from 0.01 (for *'Female head-house'*) to 0.34 (*'Head-house on health public assistance'*) with a mean value of 0.16 and a median of 0.18. These values, which make good intuitive sense, indicate that there is sufficient between-neighbourhood variability to warrant an explicit multilevel analysis.

Step 3. Performing simultaneous exploratory factor analysis at the household and neighbourhood-level

Table 19 shows the results of the two-level exploratory factor analysis. The correlation between the variables *'Less than 5 years living in the nhood'* and *'Rented house'* is greater at the household-level than at the neighbourhood-level, being even negative at the latter level. This result suggests that these two variables are measuring a different dimension than the others, and that the dimension related to residential instability is stronger at the household-level than at neighbourhood-level. Greater correlations among the other variables are observed at the neighbourhood-level, ranging from 0.24 between *'Head-house on public assistance'* and *'Female head-house'*, to 0.92 between *'None Professional family members'* and *'Head-house with Primary education or less'*, which indicates the presence of a construct operating primarily at the neighbourhood-level of analysis.

Table 19 Polychoric Correlation Matrix of the structural variables. Matrix decomposition at the household and neighbourhood level

Variable	1	2	3	4	5	6	7
HOUSEHOLD LEVEL CORRELATION							
1. Female head-house	1.00						
2. Head-house on public assistance	0.30	1.00					
3. Head-house with Primary education or less	0.08	0.11	1.00				
4. None Professional family members	0.11	0.16	0.25	1.00			
5. One or more family members is unemployed	0.07	0.22	0.04	-0.01	1.00		
6. Rented house	-0.03	0.07	-0.06	-0.05	-0.03	1.00	
7. Less than 5 years living in the nhood	-0.06	-0.01	-0.06	-0.08	-0.01	0.33	1.00
NEIGHBOURHOOD LEVEL CORRELATION							
1. Female head-house	1.00						
2. Head-house on public assistance	0.24	1.00					
3. Head-house with Primary education or less	0.42	0.83	1.00				
4. None Professional family members	0.55	0.83	0.92	1.00			
5. One or more family members is unemployed	0.32	0.52	0.60	0.55	1.00		
6. Rented house	0.49	0.29	0.42	0.55	0.26	1.00	
7. Less than 5 years living in the nhood	0.01	-0.06	-0.00	-0.10	-0.33	-0.11	1.00

The next step is to perform a two-level exploratory factor analysis which simultaneously explores the structure of the data at the household and neighbourhood-level. Between one and three factors are considered at both levels, with the results given in Table 20. Based on the fit statistics, there are two candidate models: Model 3 with three factors at the household-level and one factor at the neighbourhood-level; and Model 2 with two factors at the household-level and one factor at the neighbourhood-level.

Table 20 Two-level exploratory factor analysis model result for neighbourhood variables

				SRMR	
Model	**Within-level factors**	**Between-level factors**	**RMSEA**	**WITHIN**	**BETWEEN**
1	1	1	0.04	0.09	0.09
2	**2**	**1**	**0.03**	**0.05**	**0.09**
3	**3**	**1**	**0.01**	**0.01**	**0.09**
4	1	2	0.05	0.09	0.06
5	2	2	0.03	0.05	0.07
6*	3	2	0.01	0.01	0.07
7	1	3	0.05	0.09	0.01
8*	2	3	0.04	0.05	0.01
9*	3	3	0.00	0.01	0.01

*There are no significant factor loadings for the second neighbourhood factor.

Step 4. Performing multilevel confirmatory factor analysis

Considering the results from the two-level exploratory factor analysis, two configurations of the factor structure are examined at this step:

1) The first fitted model is based on Model 3, which factors loadings are shown in Table 21. In this confirmatory step, variables with loadings ≤ 0.30 are constrained to zero. A simple structure is imposed on the factors, that is, the factor loadings of each variable are allowed to load onto one, and only one, factor. The first factor at household-level is specified to consist of the following variables: *'Female-head household', 'Head-house on public assistance'* and *'One or more family members is unemployed'. 'Head-house with Primary education or less'* and *'None Professional family members'* define the second factor, and, *'Rented house'* and *'Living for less than five years in the neighbourhood'* constitute the third factor. The single factor at the neighbourhood-level is specified to be constituted of all variables with the exception of 'Living *for less than five years in the neighbourhood'.*

Table 21 First solution (Model 3): Three-factors at household-level and one-factor at neighbourhood level

Variables	**Household-level factors**			**Neighbourhood-level factors**
	Factor 1	**Factor 2**	**Factor 3**	**Factor 1**
1. Female head-house	0.44	0.09	-0.08	0.51
2. Head-house on public assistance	0.86	0.09	0.03	0.80
3. Head-house with Primary education or less	0.11	0.31	-0.09	0.93
4. None Professional family members	0.10	0.83	-0.03	1.02
5. One or more family members is unemployed	0.30	-0.04	-0.06	0.62
6. Rented house	0.07	-0.04	0.68	0.48
7. Less than 5 years living in the neighbourhood	-0.02	-0.07	0.49	-0.11

2) The second model is based on Model 2 shown in Table 22. Again, a simple structure is specified with a different set of constraints. For the first factor at household-level, the loadings for the variables *'One or more family members is unemployed', 'Rented house'* and *'Less than 5 years living in the neighbourhood'* are constrained to zero. For the second factor the constraint

is reversed, allowing only free estimation of the loadings for *'Rented house'* and *'Less than 5 years living in the neighbourhood'*. For the single factor at neighbourhood-level, unconstrained loadings are allowed in all the variables with exception of the variable, *'Less than 5 years living in the neighbourhood'*.

Table 22 Second solution (Model 2): Two-factors at household-level and one-factor at neighbourhood-level

Variables	Household-level factors		Neighbourhood-level factors
	Factor 1	Factor 2	Factor 1
1. Female head-house	0.40	-0.01	0.51
2. Head-house on public assistance	0.53	0.13	0.80
3. Head-house with Primary education or less	0.41	-0.17	0.93
4. None Professional family members	0.47	-0.14	1.00
5. One or more family members is unemployed	0.12	-0.02	0.62
6. Rented house	0.03	0.62	0.48
7. Less than 5 years living in the neighbourhood	-0.06	0.52	-0.11

In order to ensure a unique identifiable solution in each model and to define the metric of the latent variables, the factor variances of the specified models at both levels are constrained to 1. To compare these two alternative models, the Bayesian information criterion (BIC) is used, with smaller values indicating a better fitting model (Kang and Cohen, 2007). From Table 23 it is clear that Model 3 is the better fit to the data. The goodness of fit statistics of this model suggest an adequate fit with the values of the CFI, TLI and the RMSEA in the expected range. Consequently, the results strongly suggest that three dimensions of structural conditions at the household-level and one dimension at the neighbourhood-level is the best factor structure to reproduce the observed relationships among the seven variables.

Table 23 Goodness-of-fit statistic for two-level factor models related to neighbourhood structural characteristics

Model	Description	BIC	CFI	TLI	RMSEA
2	Two-factors at household-level and one-factor at neighbourhood-level	150558.0	0.837	0.764	0.025
3	Three-factors at household-level and one-factor at neighbourhood-level	150200.0	0.975	0.960	0.010

Focusing on the standardized factor loadings of the chosen model shown in Table 21, it is clear that larger loadings values are found at the neighbourhood-level, indicating the presence of a construct with a stronger meaning at this level than at household-level. At neighbourhood-level, the loadings of the single factor are fairly homogeneous, with exception of the variable *'Less than 5 years living in the neighbourhood'* which shows a low and non-significant loading. This factor can be labelled 'neighbourhood deprivation'. At the household-level, there are three variables with high loadings on Factor 1 (*'Female head-house', 'Head-house on public assistance'* and *'One or more family members is unemployed'*) which thus can be labelled 'concentrated disadvantage'. Factor 2 has only two variables with strong loadings (*'Head-house with Primary education or less'* and *'None Professional family members'*) and this can be labelled 'non-professional families'. Finally, Factor 3 has high loadings on two variables (*'Rented house'* and *'Less than 5 years living in the neighbourhood'*) and can be labelled 'residential instability'. The correlation between the household factors of concentrated disadvantage and non-professional families is positive and significant (0.39), indicating than families who are disadvantaged also tend to be non-professionals. A negative correlation is estimated between the non-professional and residential instability household factors (-0.19), indicating that non-professional families tend to be more stable in their neighbourhood of residence.

Step 5. Estimating an ecometric model to obtain neighbourhood scores and assess their ecometric properties

The next step is to use the six variables (out of the seven original variables) to estimate the variance and covariance of the neighbourhood deprivation construct, the latent score for each neighbourhood and to evaluate its ecometric properties. This is done by fitting the ecometric model for binary variables. The model is fitted using MLwiN 2.22 software with MCMC estimation, where 500 simulations are discarded as 'burn-in' and 60,000 further simulations are undertaken to generate the distribution of interest. The MOR statistic (Larsen and Merlo, 2005), outlined in Chapter Four, is used to give a better interpretation of the neighbourhood-level variance. In this model, the household-level covariates are not included, given that the variables involved in this analysis do not reflect any individual subjective perception, rather than households' socio-economic conditions at a given time.

The results of the model show that the mean probability of a typical household being in deprivation across the city is 27.5% (95% CI 26.1% - 28.9%). There is a significant variation at both the household and the neighbourhood-level (Table 24). In particular, the variation at the neighbourhood-level is higher than at the household-level. More than half of the higher-level variation of deprivation occurs at the neighbourhood level (58%). This confirms the result of the confirmatory factor analysis about the presence of a construct with a strong empirical meaning at that level. Results also show that the MOR for a household in a neighbourhood with the higher propensity of deprivation and a household in a neighbourhood with the lower propensity of deprivation is 1.64. This value again indicates substantial neighbourhood-level variability in the differential odds of being in deprivation.

Turning to the evaluation of the ecometric properties of the deprivation construct, there is a high inter-rater agreement between households within a neighbourhood. The estimated neighbourhood reliability is 0.95, suggesting that the estimated deprivation mean is a good estimate of the true neighbourhood score.

Table 24 Random components estimates of the ecometric model

	Variance (95% credible interval)	MOR 95% credible interval	Reliability
Null model			
Neighbourhood-level variance	0.27 (0.22 - 0.33)	1.64 (1.56 - 1.72)	0.95
Household-level variance	0.20 (0.17 - 0.22)		
Proportion of higher-level variance	0.58		

Table 25 reports the results of the spatial multiple membership model. Comparisons of the DIC show substantial improvement with the inclusion of the spatial neighbour terms. The spatial variance term is highly significant (p-value <0.001) and even higher than the aspatial effects (p-value <0.01), indicating a considerable spatial clustering of the level of deprivation.

Table 25 Variance components from the spatial multiple membership ecometric model

	Variance (95% credible interval)	MOR (95% credible interval)
Spatial variance	0.98 (0.70 - 1.41)	2.56 (2.21 - 3.08)
Aspatial variance	0.05 (0.03 - 0.07)	1.23 (1.19 - 1.29)
Household-level variance	0.19 (0.17 - 0.22)	

The combination of the spatial and aspatial effects is used to derive the overall neighbourhood scores. These values are displayed on the logit scale in Figure 26. Given the negative skew of this distribution, it is worth proceeding to the sixth step to ascertain whether this heterogeneity can be better modelled by distinctive discrete subgroups at neighbourhood-level instead of a continuous distribution.

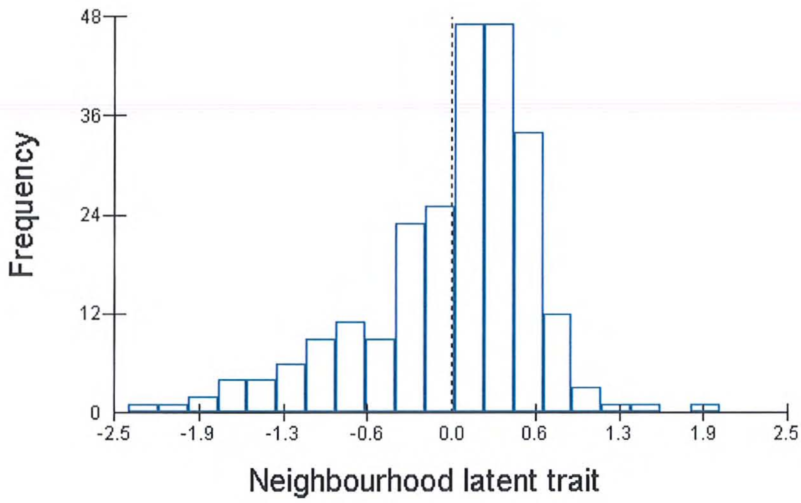


Figure 26 Frequency distribution of the estimated neighbourhood deprivation score (spatial and aspatial effects). Medellin, 2007

Step 6. Perform a multilevel latent class analysis of the neighbourhood deprivation construct

Table 26 reports the results of the multilevel latent class analysis undertaken in MPLUS. BIC values from the models without random effects (Model 1) show that a model with three classes of households is preferred solution for this data set. Much lower BIC values are observed when continuous random effects are included into this three-class solution (Model 2). Model 3 includes two neighbourhood-level latent classes, which yields a slightly higher BIC than the parametric representation. However, the very low entropy values indicate that there is a large uncertainty in classifying the neighbourhoods into these two distinct classes. The fitting of a three latent classes at the neighbourhood level (Model 4) resulted in a similar BIC and entropy value as the two class model. Overall, distinct latent classes of neighbourhoods cannot be well identified in the data. Consequently, this analysis confirms the presence of a continuous distribution of neighbourhoods on the deprivation scale and, thus, the results of the spatial ecometric model are supported.

Table 26 Sequential model comparisons for the deprivation latent trait scale

Model	Specification	Deprivation				
		Household-level				
		1 class	2 classes	3 classes	4 classes	5 classes
1	Single					
	BIC	141411.91	139198.30	138894.32	138894.90	138940.68
	Entropy		0.43	0.68	0.69	0.67
2	Random effects model parametric					
	BIC			133907.49		
	Entropy			0.81		
3	Random effects model non-parametric (2 classes nhood-level)					
	BIC		139218.15	138924.78		
	Entropy		0.33	0.39		
4	Random effects model non-parametric (3 classes nhood-level)					
	BIC		139238.00	138954.70		
	Entropy		0.22	0.73		

These estimated continuous neighbourhood scores obtained from the spatial ecometric model are portrayed in Figure 27. Purely for mapping purposes, the scores are classified into groups according to their tercile rank. Note that the darkest shade corresponds to the highest tercile, representing neighbourhoods with the highest deprivation scores, and white areas represent neighbourhoods without information. The map shows that the most deprived neighbourhoods in Medellin tend to cluster along the periphery of the city, with a substantial cluster located at the north-east side of the city.

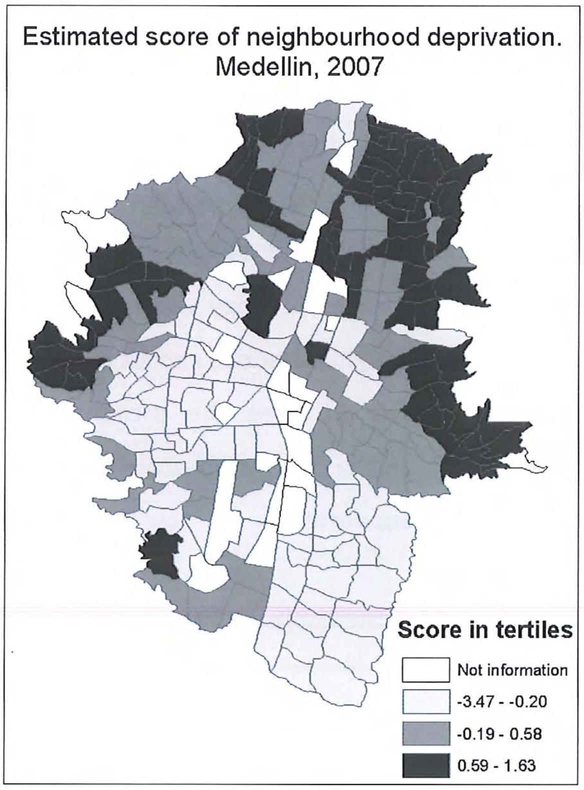


Figure 27 Distribution of the deprivation neighbourhood scores across 244 neighbourhoods. Medellin, 2007

Measuring neighbourhood social characteristics

Neighbourhood social dimensions are conceived as the problems, processes and dynamics operating within the neighbourhood. The most common constructs used to capture these aspects are: neighbourhood disorder; crime; informal social control; social cohesion; neighbourhood violence, and institutional resources. 'Disorder' has been defined as the physical signs of disorder and the unwillingness of residents to confront strangers, intervene in a crime, or call the police (Sampson et al., 2002a). 'Informal social control' describes the degree to which residents monitor or supervise the behaviour of children and young, in accordance with socially accepted practices to maintain public order (Leventhal and Brooks-Gunn, 2000). 'Social cohesion' relates to conditions of mutual trust and shared expectations among neighbours (Sampson et al., 1997). 'Perceived violence' refers to the residents' perception of violence in the neighbourhood. Finally, 'institutional resources' refers to the quality, quantity, and diversity of institutions in the community (Molnar et al., 2008).

In this section of the chapter, the interest is to create reliable social neighbourhood variables for the Medellin neighbourhoods, using data from a second community survey. To do so, the six-step procedure described above is again applied.

The data

Survey of Dimension and distribution of different kinds of violence

This is a cross-sectional household survey conducted in 2007 by the University of Antioquia in the Valle de Aburra cities of Colombia, which has detailed information for 2,095 individual adults on the experience of violence, neighbourhood conditions, and social relationships in the local neighbourhood. This study used a multistage sampling design to generate a representative sample of the population aged 12 to 60. In the first stage of the design, a random sample of blocks (*manzanas*) is selected in a way that their probabilities of selection are proportional to the relative size of the population aged 12 to 60 in each *comuna*. At the second stage, 12 residents are randomly selected within each block and interviewed in person. Of the 2,095 respondents to the survey, this study analyzed data from 1,926 (91.9%) residing in 126 neighbourhoods who answered all the variables rating social neighbourhood constructs. The mean age of the respondents is 33 years, 57% of them are female, 43% are from the lowest social class stratum while 12% from the highest. On average, respondents had lived 16 years in their neighbourhood and 58% lived in their own house.

Based on the literature discussed in Chapter Two, the survey variables are grouped into five potential social neighbourhood constructs:

Physical and social disorder is measured by asking people to indicate how much of a problem for the neighbourhood is : i) garbage, litter or broken bottles on street or sidewalk, ii) selling or using drugs, iii) drunk people in the street, iv) teenagers causing a disturbance, and v) presence of gangs or armed groups. Residents could respond using a three-category Likert response scale: 'not a problem', 'some problem' and 'serious problem'.

Informal social control dimension: respondents are asked to what extent the following are experienced in their neighbourhood: i) residents help in the surveillance of the neighbourhood, ii) residents help to look after the children in the neighbourhood; residents would intervene if children: iii) were skipping school, iv) children are hitting others, v) children are spray-painting graffiti on a local building, vi) children are showing disrespect to an adult, vii) a fight broke out in front of their house, viii) spouses are having a conjugal fight, ix) something suspicious is happening, and, x) a neighbour severely punishes his/her child. Residents could respond using a four-category Likert response scale with the following categories: 'unlikely', 'little likely', 'likely', and, 'very likely'.

Social cohesion: respondents are asked to rate, using the same four Likert categories: i) how close-knit the neighbourhood is, ii) the extent to which neighbours are willing to help each other, ii) the extent to which people in this neighbourhood can be trusted, iv) the extent to which people in this neighbourhood share the same values, v) the extent to which people in this neighbourhood get along with each other.

Institutional resources: is focused on the perception of the presence or not of the following neighbourhood resources : i) parks for children to play, ii) places for practicing your favourite sport, iii) opportunities to participate in musical and theatre activities, iv) opportunities to attend educational public talks, v) open spaces where people can walk, and vi) social rooms or communal centres.

The variables are coded so that the worst category is the highest value on the ordinal scale.

Methodology

The estimation of the neighbourhood social constructs follows the six step procedure. However, given the ordered nature of the responses for three of the four proposed scales, an ordered multinomial model is required. This model exploits the ordering of the categories in estimating the cumulative probabilities for each of the Likert response scales.

The multilevel factor model for ordered items

A three-level factor model with ordered variables is specified as (Steele and Goldstein, 2006):

$$Probit(y_{cijk}) = \propto_{ci} + \beta_0^T + \lambda_i^{(1)^T} \eta_{jk}^{(1)} + \ldots + \lambda_i^{(2)^T} \eta_j^{(2)} + u_{ijk} + v_{ik}$$

$$(c = 0, \ldots, c_i - 1)$$

$$\eta_{jk}^{(2)} \sim N(0, \Omega_{v(2)}),\ \eta_{jk}^{(3)} \sim N(0, \Omega_{v(3)}), u_{ijk} \sim N(0, \sigma_{ijk}^2),\ v_{ik} \sim N(0, \sigma_{ik}^2)$$

where y_{cijk} is the observed ordinal variable i for household j in neighbourhood k. In this model, variable i has c +1 response categories, thus if ci = 1 then i is binary and if ci > 1 then i is ordinal (with categories coded from 0 upwards). The new parameter here is $\propto_{ci}$, which is the threshold parameter that indicates the level of the unobserved Normal latent variable at which, on average, respondents would choose a category c instead of category c+1.

This latent Normal approach is even more flexible than it looks because it can also handle unordered categorical variables. Thus, in this case, a 'maximum indicant' formulation is used, whereby for a c-category variable, the MCMC estimation algorithm samples from a corresponding *c-1* dimensional multivariate Normal distribution. The approach can therefore analyse continuous and discrete responses. Full details of the algorithm are given in Goldstein *et al.*(2008).

The ecometric model for ordered items

In this ecometric model, instead of estimating the probabilities of the binary categories (yes/no), the model estimates the cumulative response probabilities of achieving a higher category for each response. This can be done by assuming that there is an underlying Normally distributed response and that for *c*-category observed responses there are *c*-1 thresholds (Leyland and Goldstein, 2001). A set of indicator variables for each category response is constructed, thus if y_{ijk} is the response to the variable *i* for household *j* in neighbourhood *k* , it is then defined as $y_{ijk}^{(c)}$; an indicator variable taking the value of 1 if y_{ijk} is less than or equal to category *c,* and 0 otherwise (Browne, 2003). The model can be written as:

$$y_{ijk} \sim OrderedMultinomial\ (Cons_{ijk}, \pi_{ijk})$$

$$y_{ijk} = \gamma_{ijk}^{(c)} = \sum_{h=1}^{c} \pi_{ijk}^{(c)}, \quad c = 1, \dots, c-1$$

$$\text{logit}\left(\gamma_{\mathrm{ijk}}^{(\mathrm{c})}\right) = \alpha^{\mathrm{c}} + \beta \mathrm{X}_{\mathrm{ijk}} + \beta X_{jk} + \mathrm{u}_{0\mathrm{jk}} + \mathrm{v}_{0\mathrm{k}}$$

$$u_{0jk} \sim N(0, \sigma^2_{u0}); \quad v_{0k} \sim N(0, \sigma^2_{v0})$$

where y_{ijk} represents the set of ordered responses for variable *i* as reported by household *j* in neighbourhood *k*. Cons is a set of 1. Here, there are *c* categories with the category *c* being the base category and *h* indexing the ordered cumulative categories. The probability of a respondent *j* in neighbourhood *k* having a response variable value of *c* to a response variable is represented by $\pi^{(c)}_{ijk}$. The third line indicates that the probabilities $y^{(c)}_{ijk}$ are related to the original variables by using a logit link function. X_{ijk} are the variables representing the *i*-1 variables in the neighbourhood scale as reported for household *j* in neighbourhood *k*. The term α^c is interpreted as the log-odds of falling into category *c* on a "typical" variable on the neighbourhood scale in the 'typical' neighbourhood. These log-odds are allowed to vary at both the household and neighbourhood levels, being represented by the two random terms: u_{0jk} and v_{0k}. The former is the household differential of the underlying latent cumulative score on the logit score and is summarised assuming Normality by the variance of σ^2_u. The other random term, v_{0k} is the neighbourhood-specific score; it is also assumed to be Normally distributed and summarised by the variance of σ^2_v. In addition to modelling the cumulative probability, the model also includes the individual covariates at household-level, represented by X_{jk}, which are used to reduce the magnitude of subjective bias in the data. Finally, the cumulative proportions have a covariance matrix given by:

$$cov\left(y^{(c)}_{ijk}, y^{(r)}_{ijk}\right) = \frac{\gamma^{(c)}_{ijk}\left(1 - \gamma^{(c)}_{ijk}\right)}{n_{ijk}}, c \leq r$$

so that the level-1 distribution is multinomial.

In practice, extending this ordered multinomial model to include spatial random effects led to estimation problems as the model did not converge.

Consequently, an approximate solution is to treat the ordinal scale as a continuous response model, and then to check the similarity of the results. The linear spatial multiple membership ecometric model is specified as:

$$y_i \sim Normal\ (XB, \Omega)$$

$$y_i = \beta_{0i} + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_{i-1} x_{i-1} + \beta x_{0i} +$$

$$\sum_{j \in Neigbour\ (i)} w_{ij}^{(4)} u_{0j}^{(4)} + u_{0\,Nhood\ (i)}^{(3)} x_{0ij} + u_{0\,Household\ (i)}^{(2)} + e_{0i}$$

$$u_{0\,Neighbour\ (i)}^{(4)} \sim N(0, \Omega_u^{(4)}) \qquad u_{0\,Nhood\ (i)}^{(3)} \sim N(0, \Omega_u^{(3)})$$

$$u_{0\,Household\ (i)}^{(2)} \sim N(0, \Omega_u^{(2)}) \qquad e_{0(i)} \sim N(0, \Omega_e)$$

where y_i is the set of responses for variable *i*, x_i are indicator variables representing the *i*-1 variables for each social scale, where the not included variable serves as the reference. Finally, the four separate random effects influencing the response categories are represented by $u_{Household\ (i)}^{(2)}$ indicating the household effect (classification 2), $u_{Nhood\ (i)}^{(3)}$ the aspatial neighbourhood effect of the neighbourhood where the household lives (classification 3) and by $u_{0\,Neighbour\ (i)}^{(4)}$ representing the effect of neighbouring areas (classification 4). The neighbour weights matrix, $w_{ij}^{(4)}$ is based on sharing a common boundary and the weights sum to 1.

Following the six-step strategy, four multilevel factor models are estimated: three with an ordered response structure (for the scales physical social disorder, informal social control and social cohesion) and one for a binary response structure (institutional resources scale). The models are fitted using MPLUS Version 6.11 software (Muthén and Muthén, 1998-2010) and MLWiN using the MCMC estimation procedure (Browne, 2003), where 5,000 simulations are defined as discarded 'burn-in', followed by a further 50,000 simulations to get the distribution of interest.

Results

Step 1. Performing single-level exploratory factor analysis.

The results of this step are reported in Table 27. According to the goodness-of-fit statistics for the single-level exploratory factor analysis, a one-factor solution suffices at neighbourhood-level for the physical social disorder scale. In contrast, a two-factor solution is suggested for the social cohesion and institutional resources scales, while a three-factor and four-factor solution is indicated for informal social control.

Table 27 Model fit for a single-level exploratory factor analysis of social processes

Factors	RMSEA	SRMR
Physical social disorder		
1	0.08	0.03
2		
3		
Informal social control		
1	0.20	0.10
2	0.10	0.03
3	0.03	0.01
Social cohesion		
1	0.15	0.03
2	0.00	0.00
3		
Institutional resources		
1	0.12	0.09
2	0.03	0.01
3		

Step 2. Estimating the intra-class correlation coefficient (ICC) for each response variable

Table 28 shows the ICC values for each of the variables included in the five social neighbourhood scales. They range between 0.03 and 0.55, with a median of 0.21, indicating sufficient variation in the responses across neighbourhoods to merit multilevel factor analysis. The constructs with the more pronounced neighbourhood differences are for physical social disorder and for institutional resources.

Table 28 Intra-class correlations from step 2 by social scale variables

Variables	ICC
Physical social disorder	
Garbage, litter or broken bottles	0.29
Selling or using drugs	0.28
Drunk people in the street	0.32
Teenagers causing a disturbance	0.28
Gangs or armed groups	0.39
Informal social control	
Surveillance the neighbourhood	0.10
Help to look after the children	0.10
Intervene if children are skipping school	0.13
Intervene if children are hitting others	0.14
Intervene if children are spray-painting graffiti on a building	0.08
Intervene if children are showing disrespect to an adult	0.12
Intervene if a fight broke out in front of their house	0.15
Intervene if spouses are having a conjugal fight	0.03
Intervene if something suspicious is happening	0.17
Intervene if a neighbour severely punishes a child	0.08
Social cohesion	
Close-knit neighbourhood	0.09
Neighbours willing to help each other	0.10
People in neighbourhood can be trusted	0.14
People in neighbourhood share values	0.14
People in neighbourhood get along	0.12
Institutional Resources	
Parks	0.55
Places for sport	0.40
Musical and theatre activities	0.31
Educational public talks	0.31
Open spaces to walk	0.41
Social rooms or communal centres	0.44

Step 3. Performing simultaneous exploratory factor analysis at the household and neighbourhood-level

Subsequently, an exploratory factor analysis using Varimax rotation is applied at the household and neighbourhood-level. For each scale, solutions are evaluated for all combinations up to four factors at the household and neighbourhood-level. The results are reported in Table 29. A two-factor solution at household-level and a one-factor solution at neighbourhood level fits well for physical social disorder, social cohesion and institutional resources. The goodness of fit statistics for these models are within the expected range, suggesting that that factor structure accounts for most of the correlation among the observed variables at the household and neighbourhood-levels. Three-factors at household-level and two-factors at neighbourhood-level would appear to be the best factor structure to represent the informal social control scale. Values of the goodness of fit statistics are within the acceptable range, with a slightly worse fit at neighbourhood-level shown by the SRMR statistic (0.07). Although adding a second or a third neighbourhood-level factor shows an improvement in the fit, there are no significant loadings on these additional factors (Table 29). Therefore, a solution with only one neighbourhood factor is preferred, even for this scale.

Table 29 Two-level exploratory factor analysis model results for social neighbourhood variables

Model number	Number of household-level factors	Number of Neighbourhood-level factors	RMSEA	SRMR Household	SRMR Neighbourhood
Physical social disorder					
1	1	1	0.09	0.04	0.02
2	2	1	0.06	0.02	0.02
3	1	2	0.10	0.04	0.00
4	2	2			
Informal social control					
1	1	1	0.15	0.09	0.15
2	2	1	0.07	0.03	0.15
3	3	1	0.03	0.01	0.15
4	1	2	0.17	0.09	0.07
5	2	2	0.08	0.03	0.07
6**	3	2	0.03	0.01	0.07
7*	1	3	0.18	0.09	0.03
8*	2	3	0.10	0.03	0.03
9*	3	3	0.03	0.01	0.03
Social cohesion					
1	1	1	0.13	0.03	0.04
2	2	1	0.00	0.00	0.04
3	1	2	0.15	0.03	0.00
4	2	2	0.00	0.00	0.00
Institutional resources					
1	1	1	0.08	0.10	0.07
2	2	1	0.03	0.02	0.07
3*	3	1	0.04	0.00	0.07
4	1	2	0.08	0.10	0.03
5	2	2			
6**	3	2	0.04	0.00	0.03
7	1	3	0.09	0.10	0.00
8	2	3			
9	3	3	0.00	0.00	0.00

*No significant factor loadings in the third neighbourhood-level factor.
**No significant factor loadings in the second neighbourhood-level factor.

Step 4. Performing multilevel confirmatory factor analysis

This step evaluates whether each of the scales of the exploratory phase is a good fit to the data through a two-level confirmatory factor analysis. As previously, a simple structure is imposed by constraining some of the model parameters (factor loadings and variances), so that all variables are specified to load onto a single factor, where variables with loadings ≤ 0.30 are constrained to zero. Those variables loading highly on more than one factor (cross-loadings) are retained for the factor where they presented the highest loading. This process ensures a unique identifiable solution in the estimation of the model. Table 30 presents the results. For each scale, the measures of goodness of fit suggest a good fit, so that the factor structures at both levels succeed in accounting for the correlations between the observed variables.

Table 30 Goodness-of-fit statistic for two-Level factor models related to neighbourhood social characteristics

Model	RMSEA	CFI	TLI
Physical Social Disorder			
Two-factors household and one-factor neighbourhood	0.05	0.98	0.96
Informal Social Control			
Three-factors household and one-factors neighbourhood	0.05	0.97	0.96
Social Cohesion			
Two-factors household and one-factor neighbourhood	0.04	1.00	1.00
Institutional Resources			
Two-factors household and one-factor neighbourhood	0.05	0.98	0.96

Table 31 shows the parameter estimates from these final models included factor loadings at both household and neighbourhood-level. Focusing on the results at the neighbourhood-level, the highly loading items for the disorder scale range from 0.88 (*'Gangs or armed groups'*) to 0.98 (*'Teenagers causing disturbance'*). For the informal social control scale, one variable failed to load highly on the factor (*'Intervene if spouses are having a conjugal fight'*) and is removed from the scale. The remaining variables form one interpretable component of the neighbourhood social environment which can be labelled 'informal social control'. For the social cohesion neighbourhood scale, all the variables defining this construct are highly interrelated with the factor. The most highly associated variables are *'People get along with each other'* and *'People share values'.* Finally, the results for the institutional resources scale show that all the variables are highly correlated with the underlying factor. The variable

'Presence of social rooms or communal centres' has the least discriminatory power, but the correlation is still high at 0.63.

Table 31 Standardized factor loadings and standard errors for the confirmatory factor analysis models of the social neighbourhood variables

	Neighbourhood-level factors
Variables	**Factor 1**
Physical social disorder	
Garbage, litter or broken bottles	0.93 (0.02)
Selling or using drugs	0.90 (0.03)
Drunk people in the street	0.97 (0.02)
Teenagers causing a disturbance	0.98 (0.02)
Gangs or armed groups	0.88 (0.03)
Informal social control	
Surveillance the neighbourhood	0.99 (0.05)
Help to look after the children	0.83 (0.06)
Intervene if children are skipping school	0.73 (0.06)
Intervene if children are hitting others	1.00 (0.03)
Intervene of children are spray-painting graffiti on a building	0.88 (0.06)
Intervene if children are showing disrespect to an adult	0.99 (0.04)
Intervene if a fight broke out in front of their house	0.93 (0.05)
Intervene if spouses are having a conjugal fight	-
Intervene if something suspicious is happening	0.77 (0.06)
Intervene if a neighbour severely punishes a child	0.40 (0.14)
Social cohesion	
Close-knit neighbourhood	0.84 (0.05)
Neighbours willing to help each other	0.85 (0.05)
People in neighbourhood can be trusted	0.93 (0.02)
People in neighbourhood share values	0.98 (0.02)
People in neighbourhood get along	1.01 (0.02)
Institutional resources	-
Parks	0.83 (0.05)
Places for sport	0.88 (0.03)
Musical and theatre activities	0.87 (0.03)
Educational public talks	0.93 (0.03)
Open spaces to walk	0.84 (0.03)
Social rooms or communal centres	0.63 (0.06)

Step 5. Estimating the ecometric model to derive neighbourhood scores and their ecometric properties

Table 32 presents the results of the random part of the ecometric models for the four social scales. There are significant differences in the perceptions of the neighbourhood social conditions between respondents within a neighbourhood. Results from the null model without any household-level variables showed that between 15% (social cohesion) and 47% (institutional resources) of the variance lay at the neighbourhood level. The two scales with the largest amount of variability at the household-level are social cohesion (85%) and informal social control (83%). Once household characteristics are taken into account, the neighbourhood-level variance is not considerable nor significantly reduced for any of the scales. Neighbourhood-level random effects variances decreased by less than 20%. This adjusted analysis shows that there are differences in the propensity to perceive the social neighbourhood scales according to household characteristics (results not shown). Males more often report higher levels of social cohesion than females. Older people generally perceive lower levels of physical social disorder and higher levels of informal social control and social cohesion. A lower perception of physical social disorder is also observed as socio-economic class increases, as well as higher perceptions of neighbourhood informal social control and social cohesion. Residents who have lived in the neighbourhood for less than five years perceive lower levels of physical social disorder. Being an owner occupier does not affect any of the scales. There are no significant differences in the household perception variables for the institutional resources construct.

Table 32 Variance components of a ecometric model with and without covariates for the social neighbourhood scales

	Physical and social disorder	Informal social control	Social cohesion	Institutional resources
	Variance (95% credible interval)	Variance (95% credible interval)	Variance (95% credible interval)	Variance (95% credible interval)
Null model				
Neighbourhood-level variance	2.88 (2.05 - 3.98)	0.69 (0.46 - 0.99)	0.98 (0.62 - 1.44)	2.66 (1.93 - 3.61)
Household-level variance	4.61 (4.10 - 5.18)	3.27 (2.99 - 3.57)	5.66 (5.13 - 6.23)	2.97 (2.59 - 3.39)
Proportion of higher-level variance	0.38	0.17	0.15	0.47
Model with household-level covariates				
Neighbourhood - level variance	2.06 (1.42 - 2.90)	0.65 (0.43 - 0.94)	0.80 (0.48 - 1.21)	2.65 (1.91 - 3.62)
Household-level variance	4.55 (4.02 - 5.12)	3.23 (2.96 - 3.53)	5.52 (5.00 - 6.08)	3.00 (2.59 - 3.44)
Proportion of higher-level variance	0.31	0.17	0.13	0.47

The values given in the estimates are the medians of 50,000 chains, with a burn-in of 500. The limits of the 95 percent credible intervals are 2.5% and 97.5% points of the distribution of the chains.

With regard to the ecometric properties of the constructs, the inter-rater agreement coefficients expressed as a proportion of higher-level variance at neighbourhood-level in Table 32 show that, after adjusting for household characteristics, the neighbourhood scales for institutional resources and physical and social disorder are the ones with the highest level of agreement, that is the measures with the highest validity. The reliability coefficients shown in Table 33 indicate that there is enough between-neighbourhood variability to produce reliable neighbourhood measures.

Table 33 Reliability at the neighbourhood-level for the social neighbourhood scales

Scale	Reliability
Physical and social disorder	0.95
Informal social control	0.91
Social cohesion	0.86
Institutional resources	0.98

Next, the ecometrics model is extended to a spatial multiple membership model to improve the neighbourhood estimations and in turn their reliabilities. The results of the goodness model of fit statistic for each of the multiple membership spatial models are shown in Table 34. For the majority of the scales, there is little difference in the DIC values between the models with spatial effects and the models with aspatial effects, suggesting that the spatial model does not represent a significant improvement.

Table 34 Random parameter estimates and goodness of fit statistics for the spatial multiple membership model

	Random part estimates		DIC diagnosis	
Scale	Neighbourhood random effects $\Omega_{u}^{(3)}$	Spatial random effects $\Omega_{u}^{(4)}$	Neighbourhood random effects only	Neighbourhood random and spatial MM effects
Physical and social disorder	0.04 (0.01)	0.09 (0.04)	16104.13	16104.32
Informal social control	0.04 (0.02)	0.04 (0.03)	18576.03	18576.32
Social cohesion	0.02 (0.01)	0.03 (0.02)	15637.38	15637.99
Institutional resources*	2.05 (0.60)	1.38 (1.24)	9456.07	9456.71

*Fitted as a logistic model.

The precision-weighted neighbourhood scores from the ecometric models are displayed in Figure 28. A visual examination of the histogram suggest that the assumption of approximate Normality of the neighbourhood random effects is met for all the scales, and as such that the scores derived from the ecometric models are an acceptable representation of the neighbourhood underlying propensities.

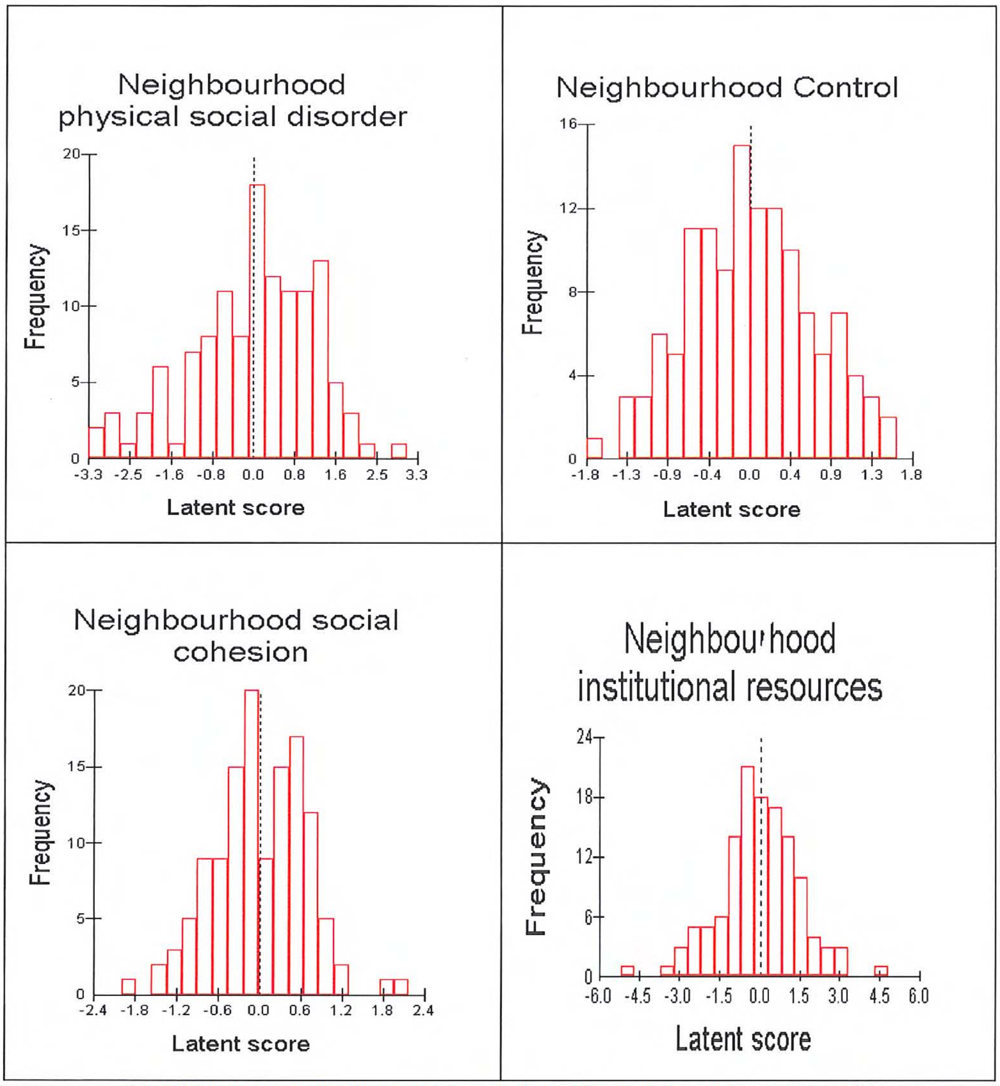


Figure 28 Frequency distribution of the social neighbourhood scores. Medellin, 2007

Finally, Figure 29 maps the distribution of the scores with terciles as cut-offs, where the third tercile indicates the 33% of the neighbourhoods with the highest social neighbourhood scores for each of the social dimensions. The north of the city has many neighbourhoods perceived as most disordered (physically and socially). Furthermore, the same area has the highest levels of social cohesion and informal neighbourhood control as well as with highest levels of institutional resources.

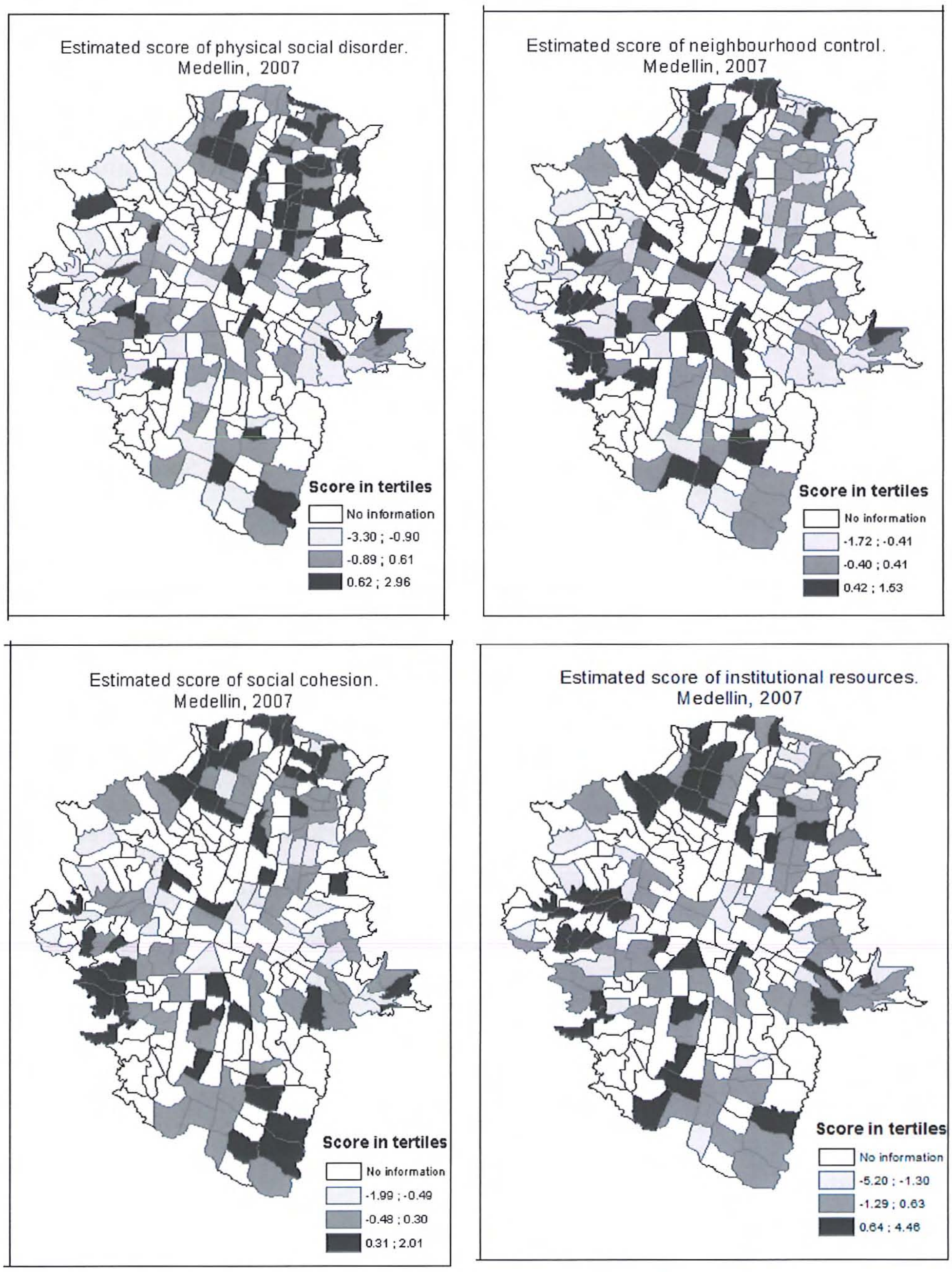


Figure 29 Distribution of the social neighbourhood scores across 126 neighbourhoods. Medellin, 2007

Measuring accessibility to community resources

Neighbourhood accessibility to community resources broadly refers to the ease with which residents of a given neighbourhood can reach civic amenities (Hewko et al., 2002). As a complement to the 'perceived presence of institutional resources' measured previously, this section considers a less subjective measure of accessibility in the form of the number of facilities within each neighbourhood. This is achieved through a GIS framework which permits the integration of data gathered from different institutions in different formats. One constraint in this study is that the exact address of the adolescents is not available, only their neighbourhood. Consequently, counts of the number of facilities within each neighbourhood and within adjacent neighbourhoods are calculated as proxies of accessibility.

The data

Neighbourhood accessibility resources are grouped into three selected domains: recreational, security and social/cultural facilities; see Table 35. Some of these locations of facilities are readily available in a GIS format; for the other data sets, the addresses were geocoded to their neighbourhood by the present researcher. As can be seen from the Table, most of the data are obtained from the City Major Office (Municipal Department of Planning) who provided a dataset in a GIS format. A list of local and public libraries, museums and theatres by address was obtained from the Directory of Medellin libraries and cultural places available on the internet (Medellín, 2010). Finally, a list of parks and green zones for recreation was obtained from the Aburra Valley Metropolitan Area.

Table 35 Summary of data collected to calculate institutional resources for each neighbourhood Medellin, 2006-2007

Community resources	Source of data	Year collected	Number of recorded facilities
Parks and recreational amenities			**443**
Parks and leisure places	Aburra Valley Metropolitan Area & Municipal Department of Planning	2005-2006	443
Security and policing			**41**
Police stations/ justice services	Municipal Department of Planning	2006	41
Social and cultural facilities			**124**
Botanic garden	Municipal Department of Planning	2006	1
Community cultural centres	Municipal Department of Planning	2006	19
Libraries	Municipal Department of Planning & City Directory	2006-2008	54
Museums	Municipal Department of Planning & City Directory	2006-2008	16
Theatres	Municipal Department of Planning & City Directory	2006-2008	34

Methodology

Adjacency matrix

The calculation of an accessibility index requires an adjacency matrix which is a symmetric array of data that relates each neighbourhood to its neighbours, defined as the areas that share a common boundary. This is operationalized by building a spatial dataset of Medellin in ArcGIS 10 software (ESRI, 2010) with attribute data related to the number of facilities within each neighbourhood. The Adjacency Tool for WinBUGS (Upper Midwest Environmental Sciences Center, 2010) in ArcGIS 10 software (ESRI, 2010) is used to identify the spatial neighbours and to count the number of facilities within each neighbourhood and within the surrounding adjacent areas.

Results

The descriptive statistics for resultant count of the number of neighbourhood facilities in each neighbourhood and within the surrounding areas for each domain is shown in Table 36.

Table 36 Descriptive statistics of the accessibility indicators. Medellin 2006-2007

Community resources	Parks and recreational amenities	Security and policing	Social and cultural facilities
Mean	12.67	1.04	3.34
Median	9.00	1.00	2.00
Minimum	0	0	0
Maximum	72	6	26
N	3219	263	849

Figure 30 displays the distribution of the community resources across the city. The terciles represent the cut-off values of the total count of resources within the own neighbourhood alone and within the adjacent neighbourhoods. Cultural resources show spatial concentration in the north and central area. A similar pattern is found for security and policing. In contrast, greater numbers of parks and recreational facilities are found in the west of the city.

Figure 30 Distribution of the neighbourhood counts of community resources across 126 neighbourhoods. Medellin, 2006-2007

Measuring homicide rate

The most common form of violence analyzed across neighbourhood studies is homicide. Generally, counts of homicides and population at risk for geographically defined areas are used to estimate the homicide rate as an indicator of neighbourhood violence. However, given the artificial aggregation of the data, the counts of the population at risk differ considerably between neighbourhoods, leading to a spatial variability that may confound the real underlying rate of homicide events. In particular, the use of simple observed proportions may lead to problems for neighbourhoods with small population counts. Such populations tend to have extreme rates when both the denominator and the numerator are small in absolute value (Langford et al., 1999). The use of smoothed rates is an important technique to ameliorate the problem of unstable raw estimates. Essentially, this method shrinks the imprecise neighbourhood-specific rate value towards the mean rate for the surrounding neihgbourhoods (Langford et al., 1999, Clayton and Kaldor, 1987). This process is commonly referred to as 'borrowing strength', since it improves the original estimate by 'borrowing strength' from the information provided by the adjacent neighbouring spatial areas (Anselin et al., 2004). This is achieved by fitting a spatial multiple membership model.

The data

The Medellin Office of the Public Prosecutor provided information on homicide occurrences in Medellin for the years 2006 and 2007 as point locations, while the City Mayor's Office provided population counts estimated for 2006 based on the 2001 Census . The crude city rate for that period is 65 per 100,000 inhabitants. These data are incorporated in to the GIS that is built for this research.

Methodology

Smoothing estimates from a multilevel spatial multiple membership model

The spatial multiple membership model can be written as follows (Langford et al., 1999, Browne et al., 2001):

$$Y_i \sim Poisson(\pi_i)$$

$$\log(\pi_i) = Log(E_i) + \beta_0 + \sum_{j\epsilon\, Nbour1(i)} w_{i,j}^{(3)}\, v_k^{(3)} + u_j^{(2)}$$

$$\left[v_{\mathrm{k}}^{(3)}\right] \sim N(0, \sigma_v^2)$$

$$\left[u_{\mathrm{j}}^{(2)}\right] \sim N(0, \sigma_u^2)$$

where Y_i , the observed count is distributed as Poisson variable with a mean, and hence also a variance of π_i. The logarithm of this underlying count is related to logarithm of the expected number of homicides, where this value is defined as follows:

$$E_i = N_i * \frac{\sum Y_i}{\sum N_i}$$

where N_i is the number of people in each neighbourhood. The term E_i is therefore the expected number of homicides if each neighbourhood has the same underlying incidence rate. The term $Log(E_i)$ is known as an offset, and the associated parameter is constrained to 1 resulting in a model that estimates the standardised homicide rate, standardised in this case by the population of the neighbourhood. The β_0 is the incidence rate on the logarithmic scale and there are two sets of shrunken random effects, the aspatial neighbourhood effects, $u_j^{(2)}$, and the spatial effects $v_k^{(3)}$ which are based on a weights matrix $w_{i,j}^{(3)}$ which defines spatial neighbours as those with a common boundary. Both sets of effects are assumed to have a Normal distribution on the log scale and to be summarised by a variance term; σ_u^2 and σ_v^2 respectively. The standard multilevel model without spatial weights simply does not include the third classification or equivalently the σ_v^2 constrained to zero. The model is estimated in MLWiN 2.23 using MCMC estimation, with a burn-in of 500 followed by 50,000 monitoring simulations; the simulations are particularly long in relation to the number of observations as it is known that a Poisson model with a mean constrained to be equal to a variance takes a particularly long to converge in MCMC estimation.

Results

The log-rate of homicide is estimated as 0.57. In addition, as shown in Table 37, both spatial and the aspatial variance terms are highly significant, being larger for the spatial term, indicating that there is a marked spatial dependency in the homicide rates.

Table 37 Parameter estimates and standard credible confidence interval for the homicide data.

	Neighbourhood variance effects	MRR
Random Part		
Spatial	2.03 (0.91 ; 3.39)	3.63 (2.48 ; 5.37)
Aspatial	0.54 (0.34 ; 0.79)	1.94 (1.70 ; 2.24)

The MOR statistic also applies for the Poisson model, but in this case it is called the Median Mean Ratio (MMR) (Larsen, 2006). In Poisson models, a MMR equal to 1 indicates that there is no variation between neighbourhoods, while a MMR larger than 1 indicates that there is a differential incidence rate of homicide in different neighbourhoods. The measure is directly comparable with fixed-effects relative risk ratios. MMR is calculated in the same way as the MOR described in Chapter Four. The MMR estimated is presented in Table 37, which confirms that there are considerable differences between neighbourhoods in the homicide rate.

Finally, Figure 31 shows the smoothed homicide rate on the logarithmic scale for each neighbourhood. It can be seen that the Normal assumption of the random effects is approximated and thus, that this parametric specification of the model is supported by the data.

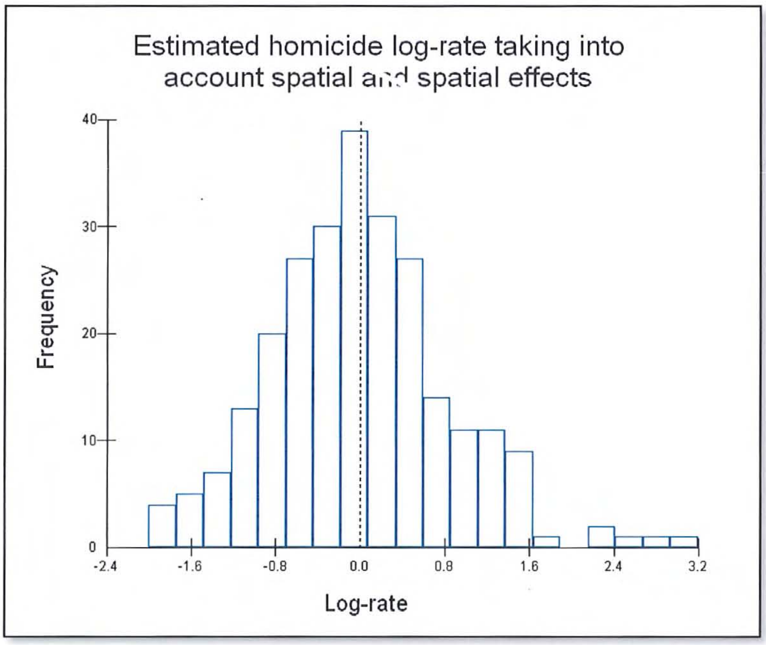


Figure 31 Frequency distribution of the smoothed homicide rate on the logarithmic scale. Medellin, 2006-2007

The map in Figure 32 shows the distribution of the estimated homicide rate on the log scale. There is a tendency for clustering, with neighbourhoods with high rates particularly in the central, north and west part of the city, whereas the zones in the south show low rates.

Figure 32 Smoothed homicide rate on the logarithmic scale across 244 Medellin neighbourhoods. Medellin, 2006-2007

Conclusions

The purpose of this chapter is to estimate reliable and valid measures of neighbourhood conditions that have been shown in previous research to contribute to the differential distribution of adolescent aggressive behaviour across communities. Data from a range of sources is used, including survey and administrative data. Most previous research that has used community survey variables for measuring neighbourhood constructs have derived the scales from the same respondents that have been surveyed for the outcome. That is, the single respondent provides both the measure of the explanatory predictors of neighbourhood characteristics and the response of individual behaviour (Sampson et al., 2002a). This methodological strategy has distinct limitations because it treats the neighbourhood measures as, in effect, individual-level characteristics rather than as emergent properties of neighbourhoods, which may increase the possibility of source bias (Mujahid et al., 2007). This study avoids this potential bias by using survey data from household informants rather than the adolescents under study. Moreover, the use of administrative data sets provides complementary data that taps a wider range of aspects of the adolescents' neighbourhood environment.

The six-step procedure and the use of a variety of statistical methods allows the estimation of nine neighbourhood constructs that characterise structural and social dimensions of neighbourhood living. The former group of characteristics is made up of seven constructs: neighbourhood deprivation; physical and social disorder; perceived availability of community resources; access to parks & recreational facilities; access to security & policing; access to social & cultural facilities and, finally the homicide rate. The latter group is composed of two constructs which describe the 'interaction' between the residents: informal social control and social cohesion.

Results from the multilevel factor analysis of the structural data show that the neighbourhood level factor solution is very dissimilar to that reported for most of the studies on neighbourhood characteristics. Six of the seven structural variables loaded strongly and positively onto the neighbourhood deprivation construct, while none of them loaded onto the residential instability construct. This result is interesting on its own and warrants further investigation about the neighbourhood-level variables that best serve as neighbourhood indicators in developing cities like Medellin. Turning to the results of the social neighbourhood constructs, the exploratory and confirmatory factor analysis demonstrated the presence of social constructs operating mainly at the neighbourhood level.

The ecometric analysis found significant variation in the probability of structural and social scores across neighbourhoods, in particular for neighbourhood deprivation, institutional resources and physical social disorder. However, there was also evidence of variation in responses within neighbourhoods, being higher for social cohesion and informal social control. As explained by Mujahid and Diez Roux (2007), this relative lack of homogeneity among households may be due to the arbitrary geographic definition of 'neighbourhoods' that is used. The householder's perception of the neighbourhood may not cohere with the defined neighbourhood, so that the neighbourhoods scales tend to vary substantively between the arbitrary defined geographic areas. However, when controlling for individual characteristics of the households the results indicate that the proportion of variation that is counted by the neighbourhood conditions did not change a great deal. Taking account of the potential subjective bias in terms of measured household characteristics did not result in a major revision of the scales. Moreover, the assessment of the ecometric properties of the resultant neighbourhood scales found reliable measurement. The reliabilities range from 0.86 to 0.98, indicating that neighbourhood scores are good estimates of the true underlying structural and social conditions of neighbourhoods. The lower neighbourhood reliabilities are observed for the informal social control and social cohesion scales, which can be attributed to their higher variation at the individual level.

Models with spatial random effects are estimated to increase the precision and reliability of the final structural and social neighbourhood scales. Results showed that, for the majority of scales, this extension is not necessary, since the inclusion of the spatial effects did not lead to an improvement of model fit. This did not apply to the deprivation scale, which show a significant improvement when the spatial effects are included. A similar spatial dependency pattern is also found for the homicide scale, indicating that there is significant spatial clustering across the city in the levels of deprivation and violence.

Table 38 gives the correlations for the estimated neighbourhood scores for all nine dimensions. In general, all correlations are in the expected direction. Informal social control, social cohesion and institutional resources are positively correlated. There is a positive correlation between neighbourhood deprivation and informal social control, indicating that neighbourhoods with higher levels of deprivation experience the highest levels of social organization. Physical social disorder is negative correlated with institutional resources, while positively correlated with homicide. Importantly in terms of using these scores as independent variables in accounting for adolescent aggressive behaviour, the correlations are not too high, so that the estimations are unlikely to be troubled by multicollinearity.

Table 38 Estimated correlations between the structural and social neighbourhood scales

	1.	2.	3.	4.	5.	6.	7.	8.	9.
1.Homicide rate	1.00								
2. Accessibility to security/policing	0.25	1.00							
3.Accessibility to parks/recreation	0.22	0.22	1.00						
4. Accessibility to culture	0.42	0.48	0.37	1.00					
5.Physical social disorder	0.11	0.14	0.05	0.24	1.00				
6.Social cohesion	-0.08	0.00	0.12	-0.09	-0.08	1.00			
7.Informal social control	0.08	0.00	0.24	-0.06	0.1	0.67	1.00		
8.Institutional resources	-0.02	-0.04	0.17	-0.12	-0.17	0.31	0.28	1.00	
9.Deprivation	0.10	0.05	-0.13	0.08	0.22	0.08	0.03	0.04	1.00

In terms of geographical patterning, neighbourhoods with the highest levels of deprivation are located in the north side of the city. A concentration of positive social processes is also found in these same areas, as is a higher level of violence. Such findings are consistent with other Latin American studies that have measured neighbourhood conditions (Villarreal and Silva, 2005). Interestingly, results from communities in economically advanced countries show a reversed pattern in the distribution of the structural and social neighbourhood characteristics; an issue that is taken up in the conclusion of the thesis.

The aims of this chapter have now been fulfilled and there are a set of uni-dimensional neighbourhood constructs of known reliability which have good measurements properties that exploit fully the available data. Overall, the constructs relate well to conceptual theories of neighbourhood differences, are not multi-collinear, have been 'purged' of household differences, and are precision-weighted (both spatially and aspatially) to minimize the effect of small neighbourhood sample sizes. As such, they should provide a good test of the effect of neighbourhood differences on the adolescent aggressive behaviour, the subject of the next chapter.

Chapter 6. Modelling individual and neighbourhood determinants of aggressive behaviour

In the previous chapters, methodologically sound measures of the dimensions of individual and neighbourhood aggressiveness have been estimated, as well as theoretically sound and methodologically reliable measures of neighbourhood characteristics. This chapter examines the role of these neighbourhood characteristics in contributing to the risk of both aggressive and delinquent behaviour. This involves assessing the extent to which neighbourhood structural and social conditions affect adolescent aggressive behaviour and in particular, the potential mediating role of neighbourhood social processes, parenting practices and peer-group influences. The analysis uses multilevel modelling and multilevel mediation modelling techniques which permit the estimation of direct and indirect effects of the neighbourhood variables. The results indicate that individual- and neighbourhood level factors are not only directly and indirectly associated with adolescent aggressive behaviour, but also that they jointly shape adolescent behaviour.

This chapter is organized in nine sections. First, a brief summary of the common approaches used to investigate neighbourhood effects on adolescent aggressive behaviour as well as their associated methodological problems are presented. This account is followed by the theoretical ecological framework developed to investigate adolescent aggressive behaviour. Third, the operationalization of the individual and family characteristics is presented. This is followed by a description of the methodological technique used to deal with the endogeneity problem that affects neighbourhood studies. The next two sections deal with the description of the two latent models used for evaluating the research hypotheses: the three-level Rasch model and the multilevel mediation model. The strategy of analysis is then detailed in the seventh section. Finally, results derived from the different models are presented and interpreted; and the chapter ends with general conclusions.

Investigating adolescent aggressive behaviour

Chapter Two reviewed the evidence on neighbourhood effects finding that there is some support for direct and indirect neighbourhood effects but in general that these effects are quite small. This is in part the result of the limited use of the multilevel capabilities for exploring richer research questions and going beyond the identification of risk factors. The studies reviewed are concerned either with: i) identifying individual and neighbourhood factors that predict differential risk or ii) understanding the neighbourhood factors that statistically explain the residual variability across neighbourhoods after taking into account the effect of individual-level variables (Diez Roux, 2000). Although such a research focus is important, many studies neglect to provide consistent answers to a broader range of neighbourhood-related questions. For example, the current available research has largely failed to properly specify the potential mechanisms that link individual and neighbourhood context, as well as the interactions between individual characteristics and neighbourhood context that potentially shape aggressive behaviour (Wikstrom and Sampson, 2003). In addition, the available research has been mostly undertaken in developed country-settings; there is little research on these issues in developing contexts.

Another limitation of the current state of the literature relates to the rationale for the selection of specific individual and neighbourhood variables; this is often not stated, or vague (Rajaratnam et al., 2006). In general, few studies have specified a unified theoretical framework that integrates individual and neighbourhood theories, and even fewer of them have fully specified the processes that operated within and between each level of analysis (Bursik and Grasmick, 1996). As pointed out by Wikstrom and Sampson (2003), researchers interested in neighbourhood influences have not properly taken into account the role of individual and family influences, just as researchers interested in individual and family influences have generally not adequately considered the role of neighbourhood influences. Advancing the study of neighbourhood-level influences on adolescent aggressive behaviour requires more than just the use of adequate methods. These must be coupled with the development of conceptual frameworks able to incorporate various levels of analysis, as well as a rigorous focus on the analysis of potential mechanisms and possible cross-level interactions. Failing to specify an appropriate theoretical framework may lead to misleading conclusions and to results that are difficult to explain.

Consequently, the aim of this chapter is to develop an integrated conceptual framework to elucidate the impact of the individual and neighbourhood variables on adolescent aggressive behaviour. The central hypothesis of this research is that structural and social characteristics -over and above individual level characteristics- contribute directly to developing and maintaining aggressive behaviour. In addition, the presence of significant differential effects of individual predictors in different neighbourhoods is hypothesized and that the effect of the structural neighbourhood conditions is transferred through neighbourhood social and individual-level processes.

Conceptual model

The conceptual framework developed for addressing this study's mediational and moderational hypotheses is shown in Figure 33. Following Mosley and Chen (1984) and Victora *et al.* (1997), this conceptual model describes the 'hierarchical relationships' between the potential determinant factors.[7] Although this strategy was originally proposed for the study of determinants of health at the individual-level, it is extended here to include neighbourhood determinants. In this

[7] Note this is not the same hierarchy as used in multilevel models, but relates to the theoretical causal ordering and 'distance' between explanatory and outcome variables. The original authors refer to the model as a *'hierarchical model'* and use the term *'hierarchical level'* to refer to the level of determination. In order to avoid confusion with the technical language of multilevel modelling, the term *'conceptual model'* replaces *'hierarchical model'* and *'blocks'* is used instead of *'hierarchical level'*.

contextual framework, both neighbourhood and individual determinants are organized into hierarchical *blocks* according to their level or causal order of determination. *Distal* refers to factors that rarely cause the outcome directly; on the contrary, they influence the outcome indirectly by acting on the more proximal factors, sometimes referred as *intermediate factors* or mechanisms. These *proximate factors* have the greatest potential to be affected by others at the same or higher levels, and may also exercise the most direct influence on the outcome of interest. The formulation of this extended conceptual model requires knowledge not only about individual and social determinants, but also about temporal considerations in that the more distal causes must operate on the more proximate outcomes, both are informed by a close reading of the literature.

Figure 33 displays the individual and neighbourhood factors to be tested in this research, organized into *blocks*. On the left of the figure are placed the individual-level variables. The first block, representing the distal variables, relates to the adolescent demographic and socioeconomic characteristics, intermediate variables relate to the education, family antecedents and experience of violence. Finally the proximal *block* includes the effect of the parenting practices and peer associations. On the right of the figure are the neighbourhood factors where the distal neighbourhood variables correspond to the structural characteristics, and the most proximal are the social neighbourhood factors.

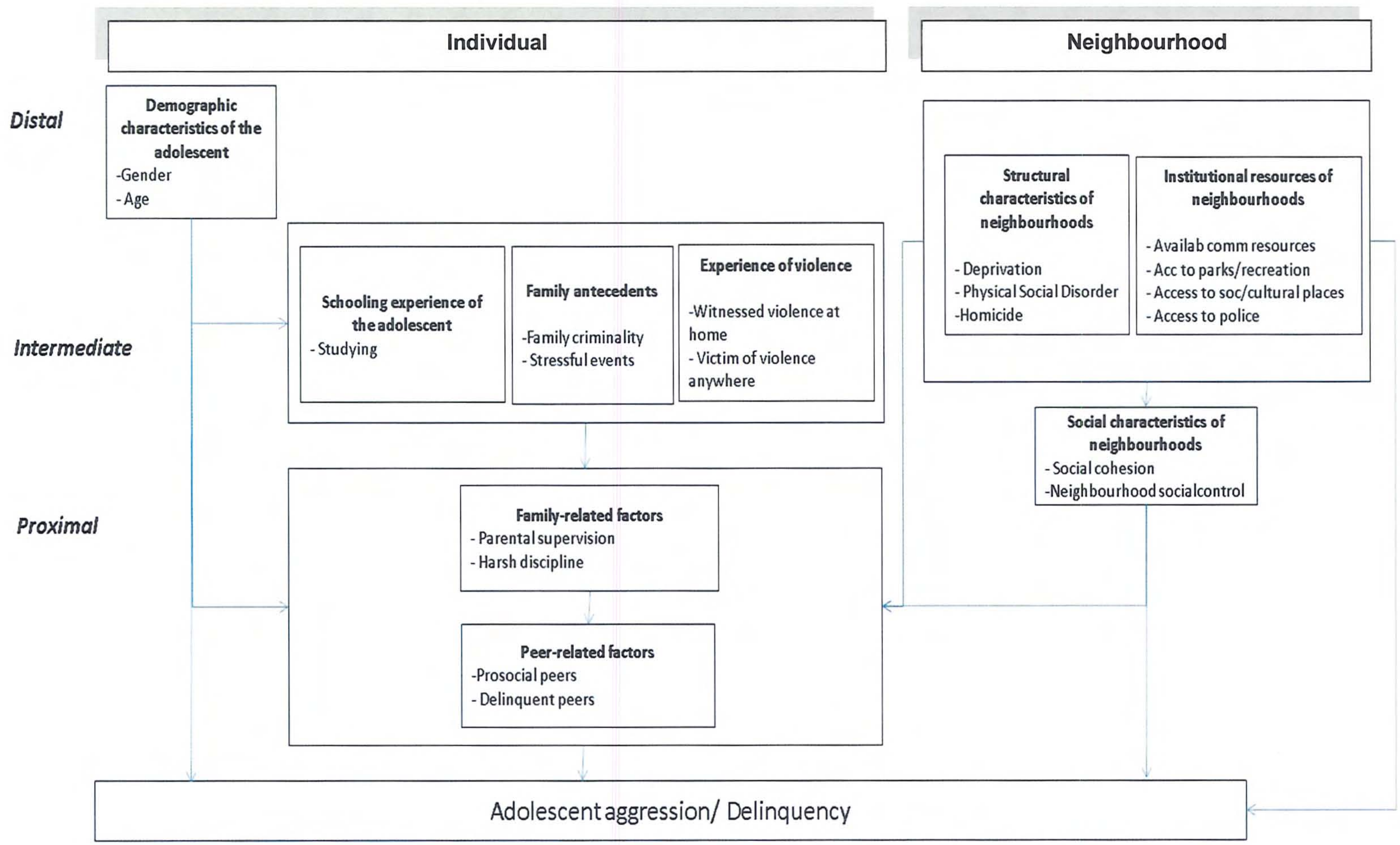


Figure 33 Conceptual model for the association between neighbourhood characteristics and adolescent aggressive behaviour

There are several advantages of using this conceptual model. In addition to the integration of individual and neighbourhood-level theories and the organization of the proximal and distal factors at both levels, the model allows the identification of the potential confounding or mediating roles of the variables, according to the research question that is being investigated. For example, in studying the effect of the neighbourhood characteristics, it is hypothesized that variables at the same level of the neighbourhood characteristics may distort such relationship, and therefore represent potential confounders. In contrast, variables that are hierarchically below the neighbourhood characteristics cannot qualify as confounders because they are partly determined by the neighbourhood structure, and therefore represent potential mediating factors. Thus, this conceptual model further specifies the 'order of entrance' of the variables into the analysis, so that the effect of any variable is adjusted *only* for confounding variables with a superior (i.e., higher block) effect, and not for all variables present in the model. For example, if the effect of neighbourhood structural variables is estimated along with the effect of family-related factors, the magnitude of the effect of the former would only reflect that part of the variation that is not mediated through parental characteristics. Therefore, it would be incorrect to interpret that structural condition of neighbourhoods as having no effect after adjustment for 'confounding' variables, since, in this model, the overall effect of structural neighbourhood conditions will be underestimated due to the presence of individual mediating factors. This conceptual ordering determines the nature of the analysis that is undertaken for the three-level Rasch model, the moderating model which involves cross-level interaction between individual and neighbourhood variables, and the multilevel mediation model that estimates indirect effects according to the hypothesized pathways.

Measuring individual and family predictors

While Chapters Three, Four and Five are concerned with the measurement of the outcome at both individual and neighbourhood-level, as well as the neighbourhood-level predictors, this section is concern with the measurement of the individual-level variables that are evaluated as confounders and mediating variables. The source of the data is the *Medellin Adolescents Survey.* Some of the variables of interest are directly measured using a single question, while others are more appropriately assessed using a set of items, which therefore have to be transformed into latent constructs. Both multilevel factor analysis and multilevel latent class analysis are again used to explore the structure of the data, to reduce the number of item indicators and to create reliable individual-level variables. Results from the analysis (not shown here) demonstrate that, for all the resultant latent individual variables, the distribution of the estimated latent true scores is discrete rather than Normal. Consequently, the latent traits are better represented as categorical variables rather than as continuous ones. Therefore, the results from the multilevel latent class analysis are used here. To determine the optimal number of latent classes, the four-step procedure described in Chapter Four is followed, where solutions with the lowest Bayesian Information Criterion (BIC) and the highest Entropy statistic are chosen as the best classifications for the data. A full description of the resultant class membership and response probabilities for each item indicator is given in Appendix 3.

Potential individual and family confounders

Based on the previous research encapsulated in Figure 1, individual-level covariates such as gender, age, educational level, family criminality, parental stress and having witnessed violence or been a victim of violence are all strongly related to adolescent aggressive behaviour. As such they may act as adolescent-level confounders in the relationship between neighbourhood conditions and adolescent aggressive behaviour. For this study they were analysed as:

- Gender: measured as dichotomous (Female, Male).
- Age: measured as ordered categorical (12, 13, 14 and 15 years since birth).
- Studying: measured as dichotomous (Studying or not).

- Family criminality: this is assessed using 8 binary variables as to whether family members (father, mother or brothers) are involved in fights with/without weapons, selling of contraband products, drug trafficking, robbery or theft, murder, and whether they have been convicted of such activities. Given the small number of adolescents answering affirmatively, adolescents are categorized as having family with criminal antecedents if there was *any* involvement in such activity.

- Parental stress: adolescents are asked about stressful life events suffered by their family during the last 12 months. They are asked whether or not: someone in their family has suffered a serious ill-health or accident; has died; has lost their job or whether the family has experienced a substantial drop in income. Latent class analysis resulted in a two-fold categorization: families who did and did not experience stressful life events in the past 12 months.

- Witness of domestic violence: this is defined with the Conflict Tactics Scale (CTS), the standard survey tool for assessing domestic violence (Straus, 1979). The adolescents are asked whether they had witnessed any of 16 violent acts in their home during the lifetime: insulted or sworn at someone; said something to spite anger or annoy; stomped out of the room, house, or yard; threatened to hit or throw something; thrown, smashed, hit, or kicked something; pushed, grabbed, shoved, slapped, kick, bitten, choked, beaten up, threatened or used a weapon against someone; and whether medical attention was needed after an argument with a family member. Results from the latent class analysis distinguished adolescents who had or had not witnessed violence at home.

- Victim of violence outside the home: this is defined by using the same set of questions as for witnessing violence. The analysis revealed an ordered latent variable with three categories of severity: never been a victim of violence or only non-severe violence, victim of moderate violence; and victim of severe violence.

Individual and family potential mediating factors

A central hypothesis is that neighbourhood effects are potentially mediated through parenting practices and peer affiliations. These are measured using the *Medellin's Adolescents Survey* on the basis of the following variables:

- *Harsh and inconsistent discipline*: defined by using a four-category Likert response scale ('Never' to 'Always') for seven items: whether been hit in the arm, hand or leg by the parent's hand, having been hit with a belt, whip, brush, stick, wire or other object, having been hit very hard and left with a bruise, bump or small cut requiring medical attention. These items produce three ordinal categories: low or no harsh punishment; moderate harsh punishment; and severe harsh punishment.

- *Parental supervision*: this is evaluated with seven items using the same four-category Likert response scale. The items are: whether their father/ mother knows where they spend their free time outside the home, with whom and what are they doing. This variable is analysed as an ordered latent construct with four categories: low supervision by both parents, low supervision by mother and high supervision by father; mother provides high supervision and father low supervision, both father and mother provide high supervision.

- *Peer deviant associations*: this is defined by using eight items, each with a Likert-scale ('All of them' to 'No one'). The adolescents are asked how many of their friends: steal or had stolen; have attacked with a knife, bottle or a weapon; belong to a gang or belong to the FARC, AUC O ELN group (Colombian armed groups). This variable is found to be a three-level ordered construct: low, moderate and high deviant influences.

- *Peer prosocial associations:* Using the same ordered Likert-scale as for deviant peers, adolescents are asked how many of their friends are religious, are the best students in their courses, practice exercise very often, are outstanding sportsmen/sportswoman, have a hobby like painting, music, reading or belong to groups that support the neighbourhood. The resultant scale is a three category scale: low, moderate and high prosocial influences.

Dealing with endogeneity problems in studying neighbourhood effects

The previous two sections of this chapter are concerned with the measurement of individual constructs, but it is crucial in a multilevel analysis that the effects of the truly individual-part of a variable (the within-neighbourhood effect) are not confounded with its analogous neighbourhood counterpart (the between-neighbourhood effect). This requires that the exogeneity assumption that individual-level predictors are not correlated with their higher-level random effects is not violated (Bauer et al., 2006). Violation of this assumption is known as endogeneity, which in general produces biased estimates of the effect of the included individual-level variables.

This endogeneity problem can result from a number of different underlying causes. This research is particularly concerned with the endogeneity that arises from omitted variable bias. In particular, there is a need to minimize the correlations between omitted unmeasured adolescent-level characteristics and the neighbourhood random effects. When this bias is present, the coefficients associated with individual-level predictors are a combination of effects at the neighbourhood and adolescent-levels. Thus, they represent the average 'within' and 'between' effects on the individual outcome. Failure to control for such endogeneity may lead to misleading conclusions about the within-neighbourhood effect, in the sense that what appears as individual effect may be in part a neighbourhood effect.

To disentangle the 'within' and 'between' effect of an individual variable, the model needs to include the neighbourhood mean value of the individual-level variable, as well as the original individual-level variable. This is known to remove the effects of cluster-level endogeneity (Jones and Subramanian, 2011, Snijders and Bosker, 1999) and to give the correct intrepretation of the individual effect, having removed the neighbourhood element. Shin and Raudenbush (2010) have developed a procedure by treating the neighbourhood mean as a latent variable. That is, the effect of the individual-level variable is estimated adjusted for its latent 'true' neighbourhood-mean, rather than by the calculated neighbourhood mean. This latent neighbourhood-mean of the individual-level covariate represents the contextual effect above and beyond the individual effect. The advantage of this approach is that the latent-neighbourhood mean takes into account the differences in the number of individuals within each higher-level unit, while allowing missingness in the covariates, which in turn increases their reliability as the neighbourhood-means are precision-weighted estimates. Consequently, a set of two-level null models are estimated with individual-level constructs, as defined above, as outcome variables. If the neighbourhood variance is statistically significant at the 5% level, the latent neighbourhood-mean is estimated and included in further models. These two-level models are estimated in MLWiN 2.13 using Markov Chain Monte Carlo (MCMC) methods.

Table 39 shows the variance and the estimated ICC for each of the individual-level variables. As expected, only gender and age do not show significant variation across neighbourhoods. While generally most of the variation of the individual predictors is between-adolescents, there are substantial neighbourhood differences for the other individual variables such as parenting practices and peer associations. Consequently, all models involving the analysis of individual-level effects (except for age and gender) are adjusted for their analogous latent neighbourhood-means.

Table 39 Neighbourhood variance of individual level predictors

Individual-level predictors	**Variance (se)**	**ICC**
Gender	0.01 (0.03)	0.42%
Age	0.02 (0.02)	0.63%
Studying	0.76(0.34)	18.67%
Family criminality	0.72 (0.36)	17.89%
Parental stress	0.51 (0.18)	13.31%
Victimized violence	1.28 (0.25)	27.96%
Witnessed violence	0.54 (0.29)	14.19%
Parental monitoring	0.82 (0.18)	19.89%
Harsh discipline	1.73 (0.37)	34.46%
Deviant peers	1.48 (0.30)	30.95%
Prosocial peers	1.19 (0.30)	26.58%

Developing the three-level Rasch model

The present research involves the investigation not only of the risk factors that affect the probability of adolescent aggressive behaviour, but also the investigation of moderational and mediational effects. In this chapter, the final three-level Rasch model developed in Chapter Four is used to explore the associated risk factors and the moderational effects, while a multilevel mediation model, which is explained in the next section, is used to explore the mediational hypothesis. Therefore, the three-level Rasch model of Chapter Four is now extended to include individual-level covariates at level-2, their neighbourhood latent-mean equivalents, the neighbourhood-level covariates (derived in Chapter Five) at level-3,[8] and the moderational effects accommodated as cross-level interactions.

Extending the three-level Rasch model in this way, rather than using the manifest version of the aggressive behaviour scales (the individual latent scores) as outcome variables in a two-level model, brings a methodological advantage. The three-level Rasch model with items at the lowest level is a measurement model. As such, it not only describes the relation between each of the aggressive behaviour items and the true latent scores for each adolescent at level-2 and

[8] As the sample design does not include multiple individual members of the family, it is impossible to estimate unexplained variation at this level. But the adolescents' questionnaire does have family variables and they will be included at the individual level.

each neighbourhood at level-3, but it also controls for measurement error. The measurement error variances are estimated simultaneously with all other model parameters, so that the estimates of the predictors are automatically adjusted for measurement error (Raudenbush and Sampson, 1999a, Raudenbush et al., 1991).

The full main effects model including individual-level predictors, their corresponding neighbourhood-latent means and the neighbourhood-level predictors, is specified as:

$$y_{ijk} \sim Binomial\ (Denom_{ijk}, \pi_{ijk})$$

$$\log e\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \beta_0 x_{0ij} + \beta_1 x_{1ijk} + \ldots + \beta_{i-1} x_{i-1jk} + \sum a_p P_{jk}$$
$$+ \sum a_q \overline{P}_k + \sum a_q W_{qk} + u_{0jk} x_{0ij} + v_{0k} x_{0ijk};$$

$$u_{0jk} \sim N(0, \sigma^2_{u0}); v_{0k} \sim N(0, \sigma^2_{v0}); \qquad Var(y_{ijk} \mid \pi_{ijk}) = \sigma^2_e \pi_{ijk}(1-\pi_{ijk})$$

where subscript *i* indicates items, *j* indicates adolescents and *k* indicates neighbourhoods. The individual and neighbourhood regression coefficients are represented by a_p and a_q respectively. The set of individual-level predictors are represented by P_{jk} and their analogous neighbourhood latent-means by $\overline{P}_k$. The set of neighbourhood-level predictors developed in Chapter Five are represented by W_{qk}. Finally, the two individual and neighbourhood-level random effects are represented by u_{0jk} and v_{0k}, which under the Rasch model correspond to the estimated latent trait varying at individual and neighbourhood level after taking account of the individual and neighbourhood predictors.

This model specification assumes that the effect of each of the individual-level variables on adolescent aggressive behaviour is independent of the neighbourhood level variables. However, moderational hypotheses, whereby neighbourhood variables may constrain or accentuate the explanatory power of individual level variables, are accommodated by extending the model to include cross-level interactions:

$$y_{ijk} \sim Binomial \quad (Denom_{ijk}, \pi_{ijk})$$

$$\log e\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \beta_0 x_{0ij} + \beta_1 x_{1ijk} + \ldots + \beta_{i-1} x_{i-1jk} + \sum a_p P_{jk} + \sum a_q \overline{P}_{pk} +$$

$$\sum a_q W_{qk} + \sum a_p P_{jk} * a_q W_{qk} + u_{0jk} x_{0ij} + v_{0k} x_{0ijk};$$

$$u_{0jk} \sim N(0, \sigma^2_{u0}); v_{0k} \sim N(0, \sigma^2_{v0}); \qquad Var(y_{ijk} \mid \pi_{ijk}) = \sigma^2_e \pi_{ijk}(1-\pi_{ijk})$$

where, P_{jk} and W_{qk} represent the corresponding main effects of the individual and neighbourhood-level predictors and their product represents the corresponding interaction term. Negative coefficients of the cross-level interaction term indicate that, in neighbourhoods with higher levels of the predictor, the influence of the individual level variable on the outcome is less strong than in other neighbourhoods. In general, this cross level interaction is easier to understand by means of a graphical display.

Developing a multilevel mediation model

The conceptual model (Figure 33 in this chapter) includes a set of mediational hypotheses involving both individual-and neighbourhood-level mediating factors. Consequently, a multilevel mediation model is required. In general, the distal independent variables are said to 'cause' the more proximal mediators or intervening variables, which in turn 'cause' the outcome variable. In classical mediation, it is anticipated that the relationship between the distal and outcome variable is reduced fully or partially due to the presence of the mediating factor; however, it can also happen that the presence of the mediator *increases* the predictive validity of the distal variable, a situation that is known as 'suppression' (MacKinnon et al., 1995). In a mediational model, the total effect of the distal variable on the outcome is decomposed into *direct* and *indirect effects*. The former refers to that part of the effect of the distal variable that is independent of the mediating factor, and the latter refers to the effect of the distal variable on the outcome that is transferred through the mediating or intervening factor (Hayes, 2009, MacKinnon et al., 2000).

The multilevel mediation model introduced by Krull and MacKinnon (2001) is the most common technique for analysing mediation with multilevel data. In this model, the variables representing the mediational processes may be measured at either or both levels of the clustered dataset, that is at the individual and neighbourhood level. Their method is also distinguished by its flexibility to include multiple mediating factors. Figure 34 illustrates the three types of multilevel mediation models typically found in research involving two mediating factors. The left side of the figure displays a single-step multiple mediator model in which the effect of the distal variable (X) on the outcome (Y) is transferred through two mediating factors which define two different causal chains or pathways (X→M1→Y and X→M2→Y). In contrast, the right side displays a multiple-step multiple mediator model or three-path model, where the effect of the distal variable is carried in part indirectly through three chains of relationships between the mediating factors (X→M1→M2→Y, X→M1→Y and X→M2→Y). In these graphs, the labels of the models are based on the hierarchical level of measurement of each of the variables involved. For example, the simplest mediation model is labelled as 1-1-1 model in which all variables are measured at the individual-level (Figure 34a). Other mediation models could be labelled as 2-1-1, indicating that only X is assessed at the neighbourhood-level while the mediating factor and outcome variable are measured at the individual-level (Figure 34b). Finally, the pathway can also be labelled as 2-2-1, in which both X and M are measured at the neighbourhood-level (Figure 34c). In these models, the α path represents the standardised regression coefficients of the effect of the *X* variable on the proposed mediator, while the β path represents the effect of the presumed mediating factors M1 and M2 on Y, while controlling for the effect of X.

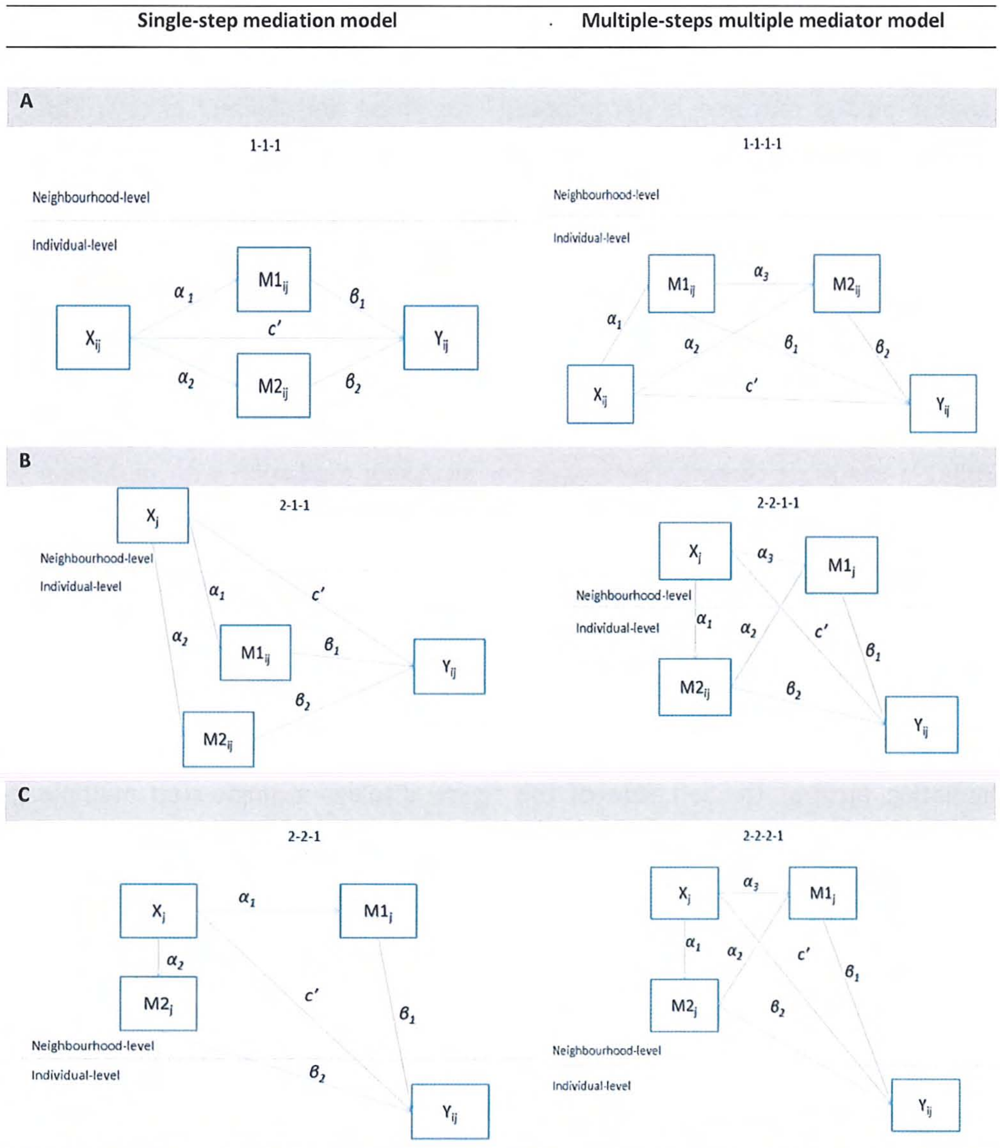


Figure 34 Multiple mediation designs under a single-step mediation model and a multiple-steps multiple mediator model. (Adapted from Krull and MacKinnon, 2001, Cheung and Lau, 2008)

The path coefficients are derived from a series of 'layered' multilevel regression equations that assess the association between: i) the distal variable and the mediating factor(s), that is the α coefficients, and, ii) the mediating factor(s) with the outcome of interest taking into account the effect of the distal variable, that is the ß coefficients. As an example with two-level Normal-theory models, the left hand side of Table 40 presents the three regression equations required for the single-step mediational models depicted in Figure 34, while the right hand side presents the equations required for a three-path mediational model.

Table 40 Multilevel equations for mediational analysis for six types of models

Single- step multiple mediational model	Multiple step multiple mediational model
1-1-1	**1-1-1-1**
$M_{1ij} = \beta_0 + \alpha_1 x_{ij} + \varepsilon_{0j}$	$M_{1ij} = \beta_0 + \alpha_1 x_{ij} + \varepsilon_{0j}$
$M_{2ij} = \beta_0 + a_2 x_{ij} + \varepsilon_{0j}$	$M_{2ij} = \beta_0 + \alpha_3 M_{1ij} + \alpha_2 x_{ij} + \varepsilon_{0j}$
$Y_{ij} = \beta_0 + \beta_1 M_{1ij} + \beta_2 M_{2ij} + c'_{ij} x_{ij} + v_{0j} + \varepsilon_{0ij}$	$Y_{ij} = \beta_0 + \beta_1 M_{1ij} + \beta_2 M_{2ij} + c'_{ij} x_{ij} + v_{0j} + \varepsilon_{0ij}$
2-1-1and 2-2-1	**2-2-1-1**
$M_{1ij} = \beta_0 + \alpha_1 x_j + \varepsilon_{0j}$	$M_{1ij} = \beta_0 + \alpha_1 x_{1J} + \varepsilon_{0j}$
$M_{2j} = \beta_0 + \alpha_2 x_j + \varepsilon_{0j}$	$M_{2j} = \beta_0 + \alpha_3 M_{1ij} + \alpha_2 x_{1J} + \varepsilon_{0j}$
$Y_{ij} = \beta_0 + \beta_1 M_{1ij} + \beta_2 M_{2j} + c'_j x_j + v_{0j} + \varepsilon_{0ij}$	$Y_{ij} = \beta_0 + \beta_1 M_{1ij} + \beta_2 M_{2j} + c'_j x_{1j} + v_{0j} + \varepsilon_{0ij}$
2-2-1 and 2-2-1	**2-2-2-1**
$M_{1j} = \beta_0 + \alpha_1 x_j + \varepsilon_{0j}$	$M_{1j} = \beta_0 + \alpha_1 x_{1J} + \varepsilon_{0j}$
$M_{2j} = \beta_0 + \alpha_2 x_j + v_{0k} + \varepsilon_{0j}$	$M_{2j} = \beta_0 + \alpha_3 M_{1j} + \alpha_2 x_{1j} + \varepsilon_{0j}$
$Y_{ij} = \beta_0 + \beta_1 M_{1j} + \beta_2 M_{2j} + c'_j x_j + v_{0j} + \varepsilon_{0ij}$	$Y_{ij} = \beta_0 + \beta_1 M_{1j} + \beta_2 M_{2j} + c'_j x_{1j} + v_{0j} + \varepsilon_{0ij}$

In these equations, the subscript *ij* represent individual *i* in neighbourhood *j*. The potential neighbourhood and individual mediating factors are represented by M_j and M_{ij} respectively. Each of the structural distal variables are represented by x_j and the unexplained variability at the individual and neighbourhood-level by ε_{ij} and v_{0j} respectively, and the intercept for each of the equations is represented by β_0. In these models c'quantifies the *direct* (or adjusted) effect of the X variable on Y after removing the effect of M. It is interpreted as the independent effect of X that is not exerted through M. The mediated or indirect effects are quantified as the product of each of the estimated α and ß coefficients that make up the mediational chain. Researchers testing multilevel mediation models with multiple mediating factors are also interested in estimating both the total indirect effect and the specific indirect effects of X on Y. For the single-step approach for example, the total indirect effect is estimated as the sum of the two specific indirect effects through M1 and M2 ($\alpha_1\beta_2$ + $\alpha_2\beta_2$). Under a multiple step multiple mediator model, the total indirect effect passing through either mediator is equal to $(\alpha_1\alpha_3\beta_2)$ + $(\alpha_2\beta_2)$ + $(\alpha_1\beta_1)$.

Cheung and Lau (2008) demonstrate that significant indirect effects can be found even if only one of the two paths is statistically significant and the second path is close to significance. Similarly, Shrout and Bolger (2002) and MacKinnon et al. (2000) demonstrate that it is appropriate to proceed with tests of mediated effects even if there is no relationship between the distal variable and the outcome. This is particularly important in cases when the presumed mediator acts as a suppressor variable (James et al., 1982). According to Shrout and Bolger (2002), even when a suppression effect is not of initial theoretical interest, it may be observed in the empirical results that the inclusion of the mediating factor increases the predictive validity of the independent variable rather than lessens it. Another situation in which the indirect effect may be significant is when the relationship between X and Y is known to be more distal. In these cases a mediational model is more powerful for detecting such distal relationships through more proximal processes (Shrout and Bolger, 2002). In these cases the analysis is said to explore the indirect effects of X on Y through M rather than the mediated effects (Hayes, 2009).

Methods to calculate the standard error of the specific and total indirect effects and their associated confidence intervals have been developed in the context of multilevel mediation by using MonteCarlo procedures (Preacher et al., 2010). These confidence intervals are automatically estimated by using Selig and Preacher's (2008) web-based utility. Confidence intervals that do not include the zero value indicate that the indirect effect is statistically significant.

The endogeneity problem discussed previously is also an issue for multilevel mediational models. In this approach the problem is known as the conflated multilevel modelling problem which results in biased estimates of the indirect effects. This problem is important in mediation designs involving at least one neighbourhood-level variable (e.g. 2-1-1), where the indirect effect can be only estimated at the neighbourhood-level. Preacher, Zyphur and Zhang (2010) developed the Multilevel Structural Equation Modelling (MSEM) to estimate such models which reduce or eliminate the conflation bias problem by separating the effect of each individual-level variable involved in the pathway chain into two parts: truly individual and neighbourhood component. MSEM partitions each observed individual variable into its latent 'within' and 'between' components allowing a straightforward separation of the within-neighbourhood effect from the between-neighbourhood effect. This allows the estimation of the direct and indirect effects at each level (Preacher et al., 2011).

This partition process is illustrated in Figure 35, where the observed variables are represented by boxes, and the corresponding latent variables at both individual and neighbourhood levels by circles. As can be seen, the figure shows a MSEM path diagram for a model under a 2-1-1 single-step mediational design that explores the mediated effect of X through M on a latent variable Y. Therefore, the only indirect effect that can occur in this model is a between-neighbourhood indirect effect. Under this model, the question of interest is not simply whether M_{ij} mediates the effect of X_j on Y_{ij}, but whether neighbourhood-level variability in M_{ij} serves as mediator of the neighbourhood-level effect of X_j on the neighbourhood-level component of Y_{ij}. To answer this question, the coefficient of the neighbourhood-path from the distal variable to the mediator, named as α_b, is estimated as is the coefficient of the neighbourhood-path from the mediator to the dependent variable, controlling for the effect of the distal variable, β_b . The corresponding indirect effect of X_j on Y_j is then estimated as α_b*β_b, which in this model is not confounded by the within-neighbourhood effect. As shown in the diagram this model can also handle responses with multiple items.

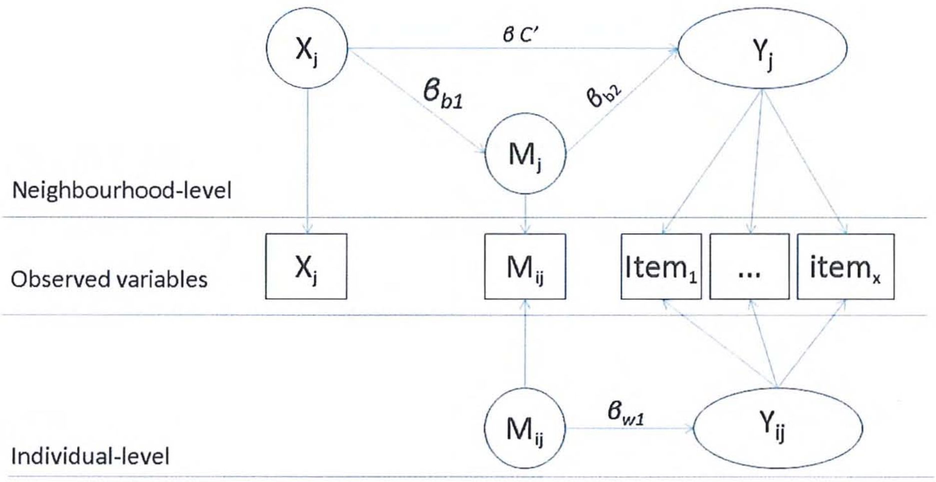


Figure 35 Multilevel structural equation modelling path diagram for a 2-1-1 mediation design (Taken from Preacher et al., 2011)

Strategy of analysis

Having highlighted the variables and statistical methods to be used in this chapter, the sequence of steps for an effective analysis that is informed by the conceptual model is now considered. The first part of the analysis investigates the overall effects of individual and neighbourhood conditions as well as potential cross-level interactions. The three-level Rasch model is used to assess the overall effect of individual variables on adolescent aggressive behaviour, adjusted by their corresponding neighbourhood latent-means. Although the models are estimated on the logit scale, they can be transformed into odds for ease of interpretation. Two forms of the model are used; Model set A gives unadjusted results and Model set B represents the adjusted analysis. The unadjusted results describe the effect of the individual predictors on aggressive behaviour corrected by endogeneity, while the adjusted results describe the effect of the individual predictors on aggressive behaviour which are additionally adjusted for the effect of variables at the same level or above in the conceptual model in Figure 1. Consequently, the analysis proceeds by including the most distal individual determinants (age and sex), followed by education, family antecedents, experience of violence and their associated latent neighbourhood-means, and finally, by the most proximal individual determinants (parenting practices and peer affiliations and their associated latent neighbourhood-means). For each block of the conceptual model, only variables with significance levels greater than 20% (z-values higher than 1.30) are retained in the analysis and variables with the lowest significance are removed on a one-by-one basis. This strategy aims to ensure that potential confounders are kept in the model, and to avoid collinearity (Maldonado and Greenland, 1993).

The next stage of the analysis additionally includes structural and social neighbourhood conditions. Consequently, Model set C investigates the independent effects of these variables conditioning on individual-level potentially confounding factors. The model uses the adjusted three-level Rasch model from Model set B excluding parenting practices and peer affiliations and their associated latent neighbourhood-means, as they are tested as mediating factors in next set of models. The model is then extended to examine the adjusted effect of the most distal structural neighbourhood variables, followed by the effect of the more proximal neighbourhood social factors. Model sets D, E and F use the three-level Rasch model from Model set C to assess the effect of the structural neighbourhood conditions, additionally adjusting for the effect of the hypothesized mediating factors: neighbourhood social conditions (Model set D), parenting practices (Model set E) and peers variables (Model set F). These factors are added sequentially in three separate blocks, representing mediators from the most distal (neighbourhood context) to the most proximal (individual) blocks. Finally, Model G investigates cross-level interactions by extending the three-level Rasch model from Model set C. All of the neighbourhood variables and their cross-level interactions with the individual variables are evaluated, but only significant terms at the 0.05 level are presented in this chapter as graphs.

The second part of the analysis is the evaluation of mediational hypotheses through a multilevel SEM approach. In this model, all regression equations are statistically adjusted for the effect of the individual-level confounding variables identified in Model set B. A single-step MSEM model is used to estimate the pathway chains from the neighbourhood structural conditions to both aggression and delinquency which is transferred through the potential mediating factors (social organization, parenting practices and peer affiliations), and the results depicted on a path diagram. Finally, a multiple-step MSEM is used to examine multiple pathway chains from the structural neighbourhood conditions to both aggression and delinquency through the potential mediation factors. This model aims specifically to test the 'parenting practices, peer affiliations and neighbourhood social network model' described in Chapter Two.

The three-level Rasch models are fitted using MCMC estimation procedures in MLwiN 2.23 which was run from STATA version 11.0 (Leckie and Charlton, 2011). Following initial maximum likelihood estimation and a burn-in period where 500 simulations were discarded, a monitoring chain of 100,000 iterations is used. The simulation is stopped when the monitoring chain of every single parameter has an effective sample size higher than 500. The MCMC procedure automatically produces 95% credible intervals of all parameters, taking account of the uncertainty of the other estimates. The MSEM models are fitted using Mplus 6.11 (Muthén and Muthén, 1998-2010) and the MonteCarlo confidence intervals for the indirect effects are estimated through the web-based utility of Seling and Preacher (2008). This program only requires the MSEM pathway estimates, standard errors, the desired level of confidence (95%) and the number of repetitions for the simulation (5,000 was used in this research) for each desired indirect effect. The estimation is done by generating an R code that is submitted to R web. The estimates produced by the differing software are on either the probit or logit scale. This is a matter of computational convenience and does not affect the interpretation of the estimates. Indeed, to convert from probit to a logit, the probit is simply multiplied by 1.61, and for conversion from a logit to a probit, multiply by 0.625 (Amemiya, 1981).

Results

The results of the multilevel analyses are presented in two main sections. The first section presents the results of the individual, family and neighbourhood risk factors as well as their cross-level interactions obtained from the three-level Rasch model. The second section gives and interprets the results from both the single-step mediation model and the multiple-step mediation model.

Results from the three-level Rasch model

Individual and family factors

Table 41 shows the results for Model A and Model B for the aggression and delinquency scale respectively. They are shown as odds ratio with their associated 95% confidence intervals, where the base or reference category is identified and set to an odds of 1. An odds in excess of 1 suggests that the associated factor increases the risk of aggression/delinquency in comparison to the base, while a factor with an odds below 1 is protective. If the confidence interval spans the odds of 1, there is no strong evidence that the factor is significantly related to aggression/delinquency. For the continuous variables such as the neighbourhood latent-means, the estimates are the change in the relative odds for a unit increase in the neighbourhood latent-mean. Again, an odds of 1 suggests no relationship and confidence intervals spanning 1 suggest no significant relation. Also given in the table for the categorical predictors are the counts of the number of adolescents in each category as this will affect the level of significance. The table also shows the median probability referring to the neighbourhood specific risk of aggression/delinquency for an adolescent in each of the categories of the individual-level variables.

For the aggression scale, unadjusted analysis (Model A) shows that, in comparison with girls and with 12 years old adolescents, boys and 15 years old adolescents are twice as likely to have engaged in aggression. Adolescents that are not studying, have witnessed domestic violence, whose family have criminal antecedents or have experienced stressful life events in the last year also show an increased odds. Similarly, the odds of aggression increase significantly as the adolescent experiences victimization, harsh discipline and relationships with deviant peers. The odds of aggression are also affected by parental supervision and relationships with prosocial peers, being around three times higher for those with low supervision from both parents and two times higher for those with low influence of prosocial peers. In regard to the unadjusted effect of the neighbourhood latent-mean variables, it is observed that the spatial concentration of adolescents with antecedents of family criminality, those who have been victims of violence, have parents experiencing stressful life events, have suffered harsh discipline and have high deviant peers significantly increase the odds of aggression. Conversely, neighbourhoods with good parental supervision reduce it.

Adjusted analyses are carried out according to the proposed conceptual model (Model B). Gender and age remain significantly associated with aggression, with boys and older adolescents having a higher risk. The effect of family criminality, witnessing or experiencing violence, parental supervision, harsh discipline and deviant peer relationships also remain significant after adjustment. The effect of studying and parental stress decrease after adjustment and are no longer significant; however, parental stress was kept it in the model as a potential confounder of variables at lower more proximal levels. It is also observed that, taking account the individual-level covariates, the neighbourhood latent-mean variables of parental stress and experiencing violent events remain positively associated with adolescent aggression. According to the results, adolescents behave more aggressively if adolescents in their neighbourhood have been victims of violence, as well as if the parents in the neighbourhood have experienced higher levels of stressful life events in the previous year (Table 41).

The results of the delinquency scale are also given in Table 41. Unadjusted results (Model A) show that boys are more likely to engage in delinquent behaviour than girls. Adolescents who are not studying are almost five times more likely to exhibit delinquent behaviour than their counterparts. Similarly, adolescents with a family involved in criminal activities or those who have witnessed or experienced violence are at significantly higher odds of delinquency in comparison with their respective reference categories. With regard to parenting practices and peer associations, adolescents with low parenting supervision, severe harsh discipline strategies, low influence of prosocial peers and high influence of deviant peers are more likely to be engaged in delinquency. Age and parental stress are not statistically associated with this adolescent outcome. In terms of the latent neighbourhood-means, neighbourhoods with higher family criminality, witnessed and experienced violence, suffered harsh discipline or have high deviant peers affiliations have significantly increase the odds of delinquency, living in neighbourhoods with high rates of supervision reduces delinquent behaviour.

The effect of gender on delinquency remains significant after adjustment (Model B); boys are more than twice more likely to be delinquents than girls. Adolescents that are not studying, have family and peers with antecedents of delinquency or have witnessed or experienced violence continue to have higher odds of delinquency, even when adjustment is made for the variables at the same or above levels. The detrimental effect also remains for those adolescents whose parents do not properly supervise them or use severe harsh discipline. However, none of the estimates associated with the neighbourhood latent-mean variables remain significant in the adjusted analysis when full account is taken of individual factors (Table 41).

Table 41 Unadjusted (Models A) and adjusted (Models B) analysis of the association between individual, parenting practices and peer-related variables with aggression and delinquency among adolescents from Medellin. 2007

		Lifetime aggression			Lifetime delinquency		
			Model A Unadjusted	Model B Adjusted§		Model A Unadjusted	Model B Adjusted§
	N	Median Probability	Odds Ratio (95% Credible Interval)	Odds Ratio (95% Credible Interval)	Median Probability	Odds Ratio (95% Credible Interval)	Odds Ratio (95% Credible Interval)
Hierarchical block 1							
Gender							
Female	870	5.0%	Reference	Reference	0.2%	Reference	Reference
Male	816	9.8%	2.06 (1.71 - 2.45)*	2.08 (1.74 - 2.46)*	0.4%	2.20 (130 - 3.40)*	2.41 (1.44 - 3.74)*
Age							
12	459	5.2%	Reference	Reference	0.2%	Reference	Reference
13	430	6.4%	1.27 (1.18 - 1.37)*	1.40 (1.10 - 1.79)*	0.2%	1.20 (0.97 - 1.50)	1.66 (0.79 - 3.06)
14	417	8.1%	1.61 (1.38 - 1.89)*	1.54 (1.21 - 1.96)*	0.3%	1.45 (0.94 - 2.24)	1.64 (0.78 - 3.07)
15	379	10.0%	2.05 (1.63 - 2.60)*	2.28 (1.77 - 2.92)*	0.3%	1.74 (0.91 - 3.36)	2.14 (0.99 - 4.05)
Hierarchical block 2							
Studying							
Not	113	11.6%	1.79 (1.27 - 2.52)*	1.21 (0.90- 1.63)	1.0%	4.66 (2.08 - 10.43)*	3.13 (1.35 - 6.32)*
Yes	1,554	6.9%	Reference	Reference	0.2%	Reference	Reference
Family criminality							
Not	1602	6.7%	Reference	Reference	0.2%	Reference	Reference
Yes	84	21.3%	3.74 (2.56 - 5.47)*	2.13 (1.52 - 2.98)*	3.5%	16.32 (6.86 - 35.70)*	7.33 (2.87 - 15.95)*
Parental stress							
Not	1433	6.7%	Reference	Reference	0.2%	Reference	Reference
Yes	253	10.3%	1.60 (1.25 - 2.05)*	1.20 (0.97 - 1.49)	0.3%	1.36 (0.69 - 2.62)	0.75 (0.35 - 1.37)
Witnessed violence							

		Lifetime aggression			Lifetime delinquency		
			Model A Unadjusted	Model B Adjusted[§]		Model A Unadjusted	Model B Adjusted[§]
	N	Median Probability	Odds Ratio (95% Credible Interval)	Odds Ratio (95% Credible Interval)	Median Probability	Odds Ratio (95% Credible Interval)	Odds Ratio (95% Credible Interval)
Not	1580	5.7%	Reference	Reference	0.2%	Reference	Reference
Yes	104	13.4%	3.09 (2.18 - 4.37)*	1.96 (1.44 - 2.67)*	1.6%	6.18 (2.44 - 13.23)*	3.23 (1.37 - 6.49)*
Victim of violence							
Minor	463	2.1%	Reference	Reference	0.0%	Reference	Reference
Moderate	957	8.1%	4.50 (3.63 - 5.58)*	4.08 (3.30 - 5.04)*	0.3%	9.25 (5.87 - 14.71)*	6.18 (2.56 - 13.17)*
Severe	266	26.8%	17.16 (12.86 - 22.91)*	11.92 (8.92 - 15.93)*	3.2%	85.48 (34.50 - 216.29)*	13.91 (10.51 - 18.34)*
Hierarchical block 3							
Parental supervision							
Low Both	569	8.7%	3.02 (2.43 - 3.74)*	1.71 (1.41 - 2.07)*	0.3%	1.35 (1.03 - 1.88)*	2.11 (1.09 - 3.94)*
Low mum & High dad	128	4.7%	1.76 (1.25 - 2.48)*	1.07 (0.79 - 1.44)	0.1%	0.55 (0.31 - 0.94)*	1.57 (0.57 - 3.44)
High mum & Low dad	328	5.8%	1.62 (1.27 - 2.06)*	1.29 (1.04 - 1.59)*	0.2%	0.74 (0.56 - 0.97)*	1.56 (0.73 - 2.97)
High Both	661	7.1%	Reference	Reference	0.2%	Reference	Reference
Harsh discipline							
Low	1163	5.8%	Reference	Reference	0.2%	Reference	Reference
Moderate	433	10.1%	2.21 (1.78 - 2.74)*	1.49 (1.23 - 1.80)*	0.5%	2.97 (1.92 - 4.65)*	2.14 (1.23 - 3.58)*
High	88	17.1%	2.51 (1.69 - 3.74)*	1.61 (1.13 - 2.28)*	1.4%	8.84 (3.67 - 21.58)*	2.56 (1.76 - 5.94)*
Hierarchical block 4							
Prosocial peers							
Low	274	9.7%	1.79 (1.38 - 2.33)*	1.15 (1.03 - 1.27)*	0.5%	3.02 (1.58 - 5.90)*	2.24 (1.04 - 4.30)*
Moderate	517	7.7%	1.06 (0.86 - 1.31)	1.33 (1.06 - 1.67)*	0.3%	1.74 (1.26 - 2.43)8	1.16 (0.62 - 1.99)

		Lifetime aggression			Lifetime delinquency		
			Model A Unadjusted	Model B Adjusted§		Model A Unadjusted	Model B Adjusted§
	N	Median Probability	Odds Ratio (95% Credible Interval)	Odds Ratio (95% Credible Interval)	Median Probability	Odds Ratio (95% Credible Interval)	Odds Ratio (95% Credible Interval)
High	884	6.1%	Reference	Reference	0.2%	Reference	Reference
Deviant peers							
Low	445	2.9%	Reference	Reference	0.1%	Reference	Reference
Moderate	1060	8.3%	2.97 (2.34 - 3.74)*	1.95 (1.57 - 2.42)*	0.3%	5.14 (3.31 - 7.92)*	1.79 (1.33 - 3.21)*
High	173	21.1%	8.82 (6.34 - 12.27)*	3.04 (2.24 - 4.12)*	1.8%	26.40 (10.95 - 62.64)*	4.25 (1.78 - 10.36)*
Neighbourhood latent-means							
Studying			0.76 (0.57 - 1.02)	1.08 (0.86 - 1.34)		0.58 (0.28 - 1.02)	0.95 (0.45 - 1.76)
Family criminality			1.51 (1.09 - 2.08)*	0.95 (0.73 - 1.23)		2.88 (1.23 - 5.99)*	0.55 (0.23 - 1.14)
Parental stress			1.59 (1.15 - 2.21)*	1.29 (1.00 - 1.64)*		1.22 (0.53 - 2.46)	0.70 (0.29 - 1.36)
Witnessed violence at home			1.22 (0.84 - 1.77)	0.92 (0.69 - 1.21)		5.79 (2.32 - 11.80)*	2.13 (0.83 - 4.48)
Victim of violence anywhere			1.88 (1.69 - 2.12)*	1.15 (1.01 - 1.32)*		2.89 (2.03 - 3.84)*	1.30 (0.86 - 1.91)
Parental supervision			0.74 (0.60 - 0.90)*	1.10 (0.97 - 1.27)		0.59 (0.36 - 0.92)*	1.21 (0.76 - 1.84)
Harsh discipline			1.40 (1.24 - 1.57)*	1.06 (0.97 - 1.17)		1.96 (1.50 - 2.56)*	1.26 (0.93 - 1.64)
Prosocial peers			0.89 (0.73 - 1.08)	0.98 (0.87 - 1.10)		0.98 (0.60 - 1.45)	0.88 (0.57 - 1.33)
Deviant peers			1.75 (1.57 - 1.95)*	1.07 (0.95 - 1.20)		1.98 (1.35 - 2.79)*	1.02 (0.65 - 1.61)
Total	1686	7.9%			0.3%		

§ Adjusted for others individual variables in the same or higher levels of the hierarchical model with z > 1.30 and by corresponding contextual effects*z-value> 1.96, p-value< 0.05

Neighbourhood-level variables

Table 42 and Table 43 show the results of the effect of neighbourhood characteristics on adolescent aggression and delinquency. These models use the neighbourhood constructs of Chapter Five, which were measured with differing units. Therefore, in order to facilitate comparison between coefficients, they are converted to z-scores by subtracting the sample mean from each variable, and dividing the result by the standard deviation. Consequently, the regression coefficients shown in Table 42 and Table 43 indicate the odds ratio (95% CI) of a change in aggression/delinquency for an increase of one standard deviation (SD) in each neighbourhood condition.

Table 42 shows the adjusted results for the aggression scale. The results of Model C show that after have taken into account the effect of individual-level confounding variables none of the structural and social neighbourhood dimensions significantly predict adolescent aggression. Models D to F additionally adjust for the effect of the presumed mediating factors. In Model D it is observed that, having controlled for neighbourhood social processes, the link between structural neighbourhood factors and aggression remains non-significant. Results are virtually unaltered when parenting practices are added to the model (Model E). However, additional adjustment by peer influences show that neighbourhood availability of community resources is significantly associated with the underlying propensity of aggression (Model F). According to the results, 1-SD increases in the level of community resources is associated with 11% reduction in the odds of aggression. A separate analysis indicates that this significant relationship is only revealed when the negative confounding effect of deviant peers is controlled for.

Table 42 Unadjusted and adjusted analysis of the association between structural and social neighbourhood conditions with aggression among adolescents from Medellin. 2007

	Lifetime aggression			
	Model C	Model D	Model E	Model F
	Odds Ratio (95% Credible Interval)	Odds Ratio (95% Credible Interval)	Odds Ratio (95% Credible Interval)	Odds Ratio (95% Credible Interval)
Hierarchical block 1				
Deprivation	1.09(0.94-1.25)	1.09(0.94-1.26)	1.06(0.93-1.21)	1.10(0.97-1.24)
Phys Social Dis	1.04(0.94-1.16)	1.05(0.94-1.16)	1.03(0.94-1.16)	1.02(0.94-1.12)
Comm. Resources	0.92(0.81-1.03)	0.90(0.79-1.00)	0.93(0.83-1.05)	0.89(0.80-0.98)*
Parks/recreation	1.08(0.97-1.20)	1.08(0.96-1.21)	1.04(0.94-1.18)	1.02(0.92-1.13)
Cultural places	0.96(0.85-1.09)	0.96(0.84-1.08)	1.00(0.88-1.13)	1.03(0.91-1.15)
Policing & Secu	1.02(0.89-1.16)	1.02(0.89-1.16)	1.01(0.89-1.16)	0.97(0.87-1.09)
Homicide	1.02(0.91-1.14)	1.04(0.92-1.16)	1.05(0.94-1.16)	1.05(0.95-1.15)
Hierarchical block 2				
Social cohesion	1.06(0.93-1.20)	-	-	-
Infor Soc Ctrl	1.02(0.89-1.16)	-	-	-

Model C: Adjustment by individual confounders with z > 1.30 in Model B (gender, age, socio-economic status, studying, family criminality, parental stress and witnessed/victimized violence).
Model D: As Model C plus adjusted by potential social neighbourhood mediators
Model E: As Model D plus adjustment by potential parenting mediators
Model F: As Model E plus adjustment by potential peer mediators
* z-value>1.96, p-value < 0.05

Results for the delinquency scale are shown in Table 43. Conditioning on individual-level confounders, none of the neighbourhood conditions appear to influence significantly the odds of delinquency (Model C). Adjustment for the presumed mediating factors shows that once social neighbourhood processes (Model D), parenting practices (Model E) and peer influences (Model F) are added into the model the non-significant results remain unchanged. Consequently, results indicate that, over and above the effect of the individual and social neighbourhood characteristics, none of the structural neighbourhood characteristics influence the underlying probability of adolescent delinquent behaviour.

Table 43 Unadjusted and adjusted analysis of the association between structural and social neighbourhood conditions with delinquency among adolescents from Medellin. 2007

	Lifetime delinquency			
	Model C	Model D	Model E	Model F
	Odds Ratio (95% Credible Interval)	Odds Ratio (95% Credible Interval)	Odds Ratio (95% Credible Interval)	Odds Ratio (95% Credible Interval)
Hierarchical block 1				
Deprivation	1.04(0.70-1.48)	1.03(0.71-1.42)	0.95(0.62-1.37)	1.00(0.64-1.49)
Phys Social Dis	1.20(0.86-1.64)	1.18(0.83-1.63)	1.11(0.76-1.50)	1.12(0.78-1.56)
Comm. Resources	0.89(0.61-1.27)	0.82(0.54-1.16)	0.81(0.54-1.23)	0.82(0.55-1.15)
Parks/recreation	1.04(0.69-1.49)	0.98(0.65-1.40)	0.95(0.62-1.40)	0.95(0.62-1.40)
Cultural places	1.16(0.73-1.70)	1,15(0.76-1.71)	1.32(0.85-2.05)	1.33(0.85-2.00)
Policing & Secu	0.75(0.40-1.13)	0.73(0.45-1.15)	0.74(0.44-1.14)	0.70(0.43-1.05)
Homicide	0.82(0.60-1.16)	0.84(0.57-1.19)	0.83(0.56-1.15)	0.84(0.55-1.22)
Hierarchical block 2				
Social cohesion	1.23(083-1.77)	-	-	-
Infor Soc Ctrl	1.05(0.70-1.53)	-	-	-

Model C: Adjustment by selected individual confounders with z > 1.30 (gender, age , studying, family criminality and witnessed/victimized violence).
Model D: As Model C plus adjustment by potential neighbourhood social mediators
Model E: As Model D plus adjustment by potential parenting mediators
Model F: As Model E plus adjustment by potential peer mediators
* z-value>1.96, p-value < 0.05

Cross-level interactions

The next stage of the analysis is deliberately exploratory and examines the possibility of cross-level interactions between individual/family variables and neighbourhood characteristics. This is undertaken because, while neighbourhood variables are shown to have no effect in general (the overall and direct effects are not significant), there may be a fraction of the adolescent population for whom the neighbourhood characteristics are important. The size and nature of the interaction effects are more easily appreciated as graphs than as estimates. The figures display all the significant interactions that are found. The vertical axis on the graph is the estimated probability of aggressive behaviour; the horizontal axis is the neighbourhood characteristic as a z-score over the full extent of its observed range and the dotted lines portray the 95% confidence intervals. The results are first presented for the aggression scale and then for the delinquency scale. As the results are modelled on the logit scale, but presented on the probability scale, they will necessarily show a degree of non-linearity which will be more marked for delinquency as the predicted probabilities of this scale are generally well below 0.2.

Figure 36 shows that the positive relationship between harsh discipline and aggression is dependent on the level of neighbourhood deprivation. Severe harsh discipline is associated with higher probability of aggression in more deprived neighbourhoods. Figure 37 shows that high homicide rates within the neighbourhood reinforce the negative influence of deviant peers on the propensity of aggression. According to the results, in neighbourhoods with high levels of homicide the presence of deviant peers is associated with a higher probability of engaging in aggression than adolescents with low deviant influences living in the same highly violent neighbourhoods. This difference is weaker and non-significant in less dangerous neighbourhoods. Figure 38 shows that the protective effect of prosocial peers on adolescent aggression is only statistically significant in neighbourhoods with low levels of social cohesion. In those neighbourhoods, adolescents with low prosocial influences have a higher probability of aggression. This gap is not statistically significant in neighbourhoods with high social bonds. Figure 39 shows that the strong association between having witnessed violence and the odds of aggression is not significantly different in neighbourhoods with high levels of social control. However, in low socially controlled neighbourhoods, adolescents who have witnessed violence have a higher probability of aggression than adolescents that have not experienced a violent situation.

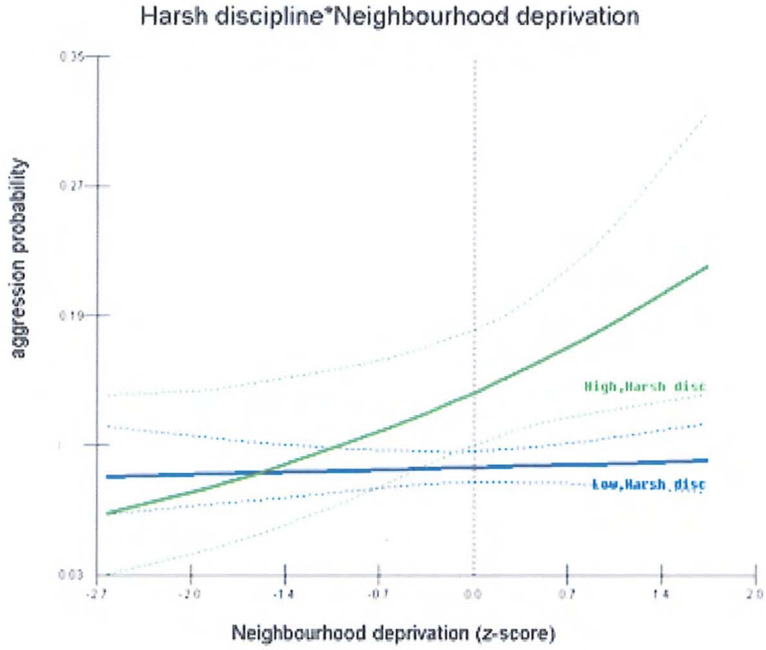


Figure 36 Cross-level interaction between parental harsh discipline and neighbourhood deprivation

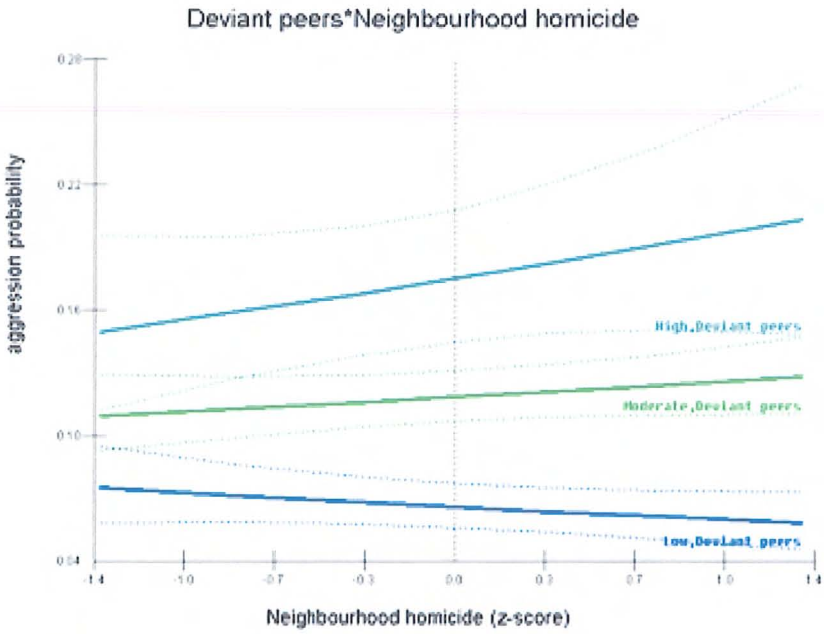


Figure 37 Cross-level interaction between deviant peers and neighbourhood homicide

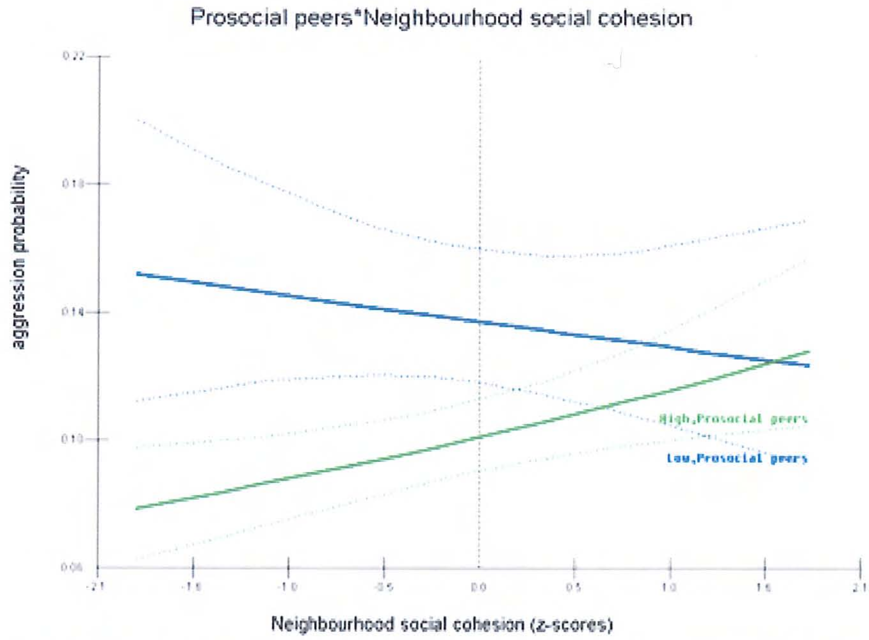


Figure 38 Cross-level interaction between prosocial peers and neighbourhood social cohesion

Figure 39 Cross-level interaction between witnessed violence and neighbourhood informal social control

Turning to the results for the delinquency scale, Figure 40 shows that in low violent neighbourhoods being associated with deviant peers has little effect on the probability of delinquency. However, where the homicide level is high, deviant peer affiliations have a stronger positive effect. Figure 41 shows that the detrimental effect of harsh discipline is also reinforced in more deprived neighbourhoods. Finally, in more violent neighbourhoods, adolescents who have witnessed a violence at home have higher probability of delinquency when compared to adolescents who live in the same neighbourhoods but that have not witnessed domestic violence (Figure 42).

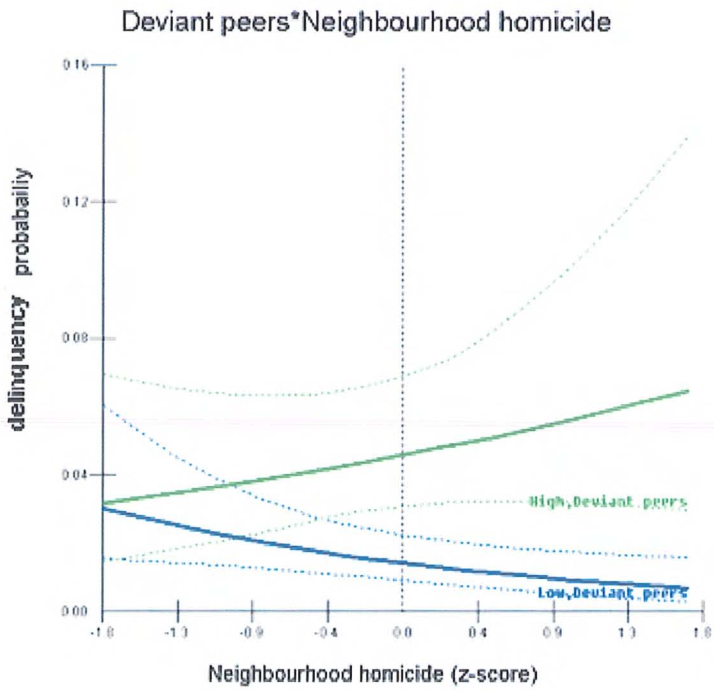


Figure 40 Cross-level interaction between deviant peers and neighbourhood homicide

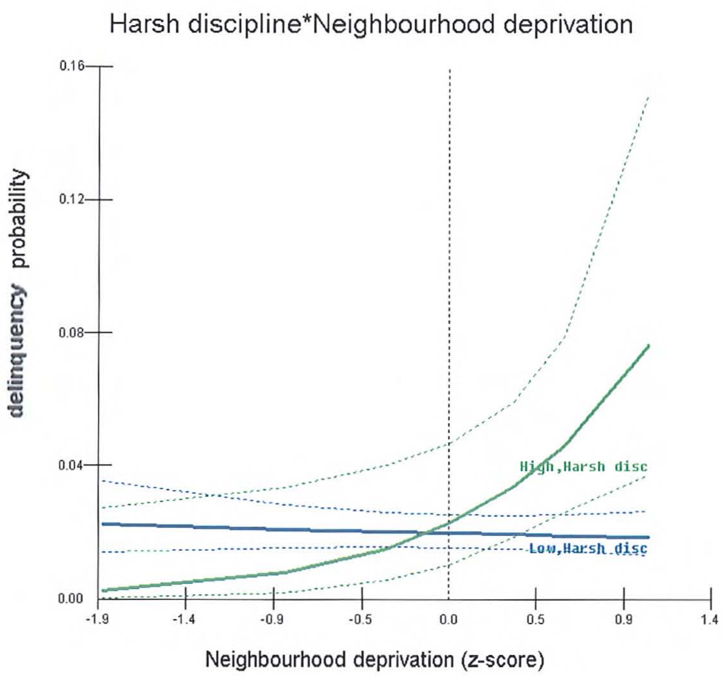


Figure 41 Cross-level interaction between harsh discipline and neighbourhood deprivation

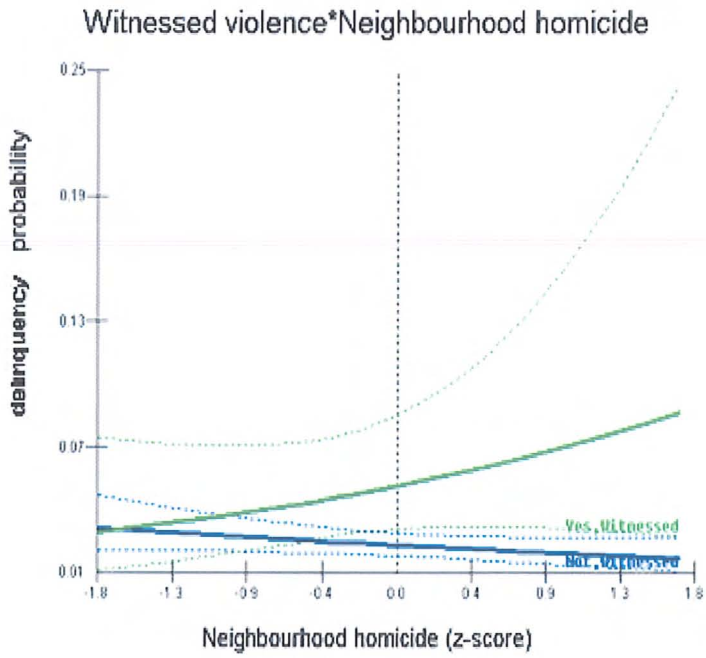


Figure 42 Cross-level interaction between have witnessed violence and neighbourhood homicide

Sources of residual variation

Results for the random part of the model, and the corresponding model fit statistics, are presented in Table 44 and Table 45 for the aggression and the delinquency scale respectively. For the aggression scale, in comparison with the null model, the inclusion of the individual variables of the first hierarchical block of the conceptual model (gender and age) lead to a large reduction in the DIC, indicating a significant improvement in the predictive capacity of the model. The unexplained neighbourhood variance is also slightly decreased, being estimated at 6.97%. The MOR estimate is larger than 1, confirming that there are sizeable neighbourhood-level differences in the odds of aggression. The DIC significantly improves with the addition of the second hierarchical block of individual variables (studying, family criminality, parental stress, having witnessed or experienced violence). The individual-level variance accounted for by this set of individual variables is 33%. Unsurprisingly, this set of individual-level variables also significantly reduced the neighbourhood-level variance by 82.9%, leaving a significant unexplained variation at the neighbourhood level of 1.61% of the total variation. However, the inclusion of the corresponding neighbourhood latent-means increased this unexplained neighbourhood variation slightly to 1.70%. Adding the third and fourth hierarchical block of individual variables (parenting practices and peers), and their corresponding analogous neighbourhood measures, also improves the DIC. The individual and neighbourhood-level variance is further reduced, resulting in a non-significant unexplained neighbourhood variation of less that 1.00%. The full model, including structural and social neighbourhood-level variables and cross-level interactions, only slightly improves the DIC, but it still does show improvement over the previous model. In total, these sets of individual and neighbourhood predictors explained some 20% of the total variation of aggression.

Table 44 Random parameters for the aggregation scale

	Individual Predictors							
		Hierarchical block 1	Hierarchical block 2		Hierarchical block 3		Hierarchical block 4	
	Null Model	Within effects	Within effects	Within and Between effects	Within effects	Within and Between effects	Within effects	Within and Between effects
	variance (SE)	variance (SE)	variance (SE)		variance (SE)		variance (SE)	
Nhood	0.41 (0.10)	0.39 (0.11)	0.07 (0.03)	0.08 (0.03)	0.06 (0.03)	0.04 (0.03)	0.02 (0.02)	0.02 (0.02)
MOR	1.84	1.81	1.30	1.31	1.25	1.23	1.14	1.14
Individ	1.84 (0.13)	1.88 (0.14)	1.23 (0.10)	1.23 (0.10)	1.20 (0.11)	1.19 (0.10)	1.12 (0.10)	1.12 (0.10)
ICC	7.40%	6.97%	1.61%	1.70%	1.21%	0.97%	0.38%	0.38%
DIC	11788	11068	10796	10790	10761	10761	10654	10656

The variance parameters are the medians of 50,000 chains with a burn-in of 500.

Continue:

	Individual and Neighbourhood predictors		Cross-level interactions
	Hierarchical block 1	Hierarchical block 2	
	variance (SE)	variance (SE)	variance (SE)
Nhood	0.02 (0.02)	0.01 (0.02)	0.01 (0.02)
MOR	1.14	1.12	1.10
Individ	1.12 (0.10)	1.12 (0.10)	1.11 (0.10)
ICC	0.41%	0.29%	0.23%
DIC	10647.653	10648.211	10642.043

Analysis of the random part of the delinquency scale (Table 45) shows that, in comparison with the null model, including the first two hierarchical blocks of individual predictors and their corresponding neighbourhood latent-means contributes considerably to both the improvement of the DIC and to the reduction of the unexplained between-neighbourhood variance, decreasing it to a significant 8.61%. Further adjustment by the third and fourth block of individual-level variables leads to a small but noticeable improvement in the DIC and substantially reduces the remained neighbourhood-level variation. The residual variance at the neighbourhood-level is then estimated as 7.14% of the total variation, though it is not significantly different from zero. The DIC shows another significant improvement with the addition of the structural and social neighbourhood variables and cross-level interactions. Together, the individual and neighbourhood-level predictors explained 19.11% of the total variation of the delinquency scale.

Table 45 Random parameters for the delinquency scale

		Individual Predictors						
		Hierarchical block 1	Hierarchical block 2		Hierarchical block 3		Hierarchical block 4	
	Null Model	Within effects	Within effects	Within and Between effects	Within effects	Within and Between effects	Within effects	Within and Between effects
	variance (SE)	variance (SE)	variance (SE)		variance (SE)		variance (SE)	
Nhood	1.66 (0.55)	1.61 (0.55)	0.91 (0.40)	0.83 (0.41)	0.66 (0.39)	0.55 (0.39)	0.69 (0.42)	0.67 (0.44)
MOR	3.40	3.35	2.48	2.37	2.16	2.02	2.21	2.18
Individ	7.26 (1.16)	7.32 (1.16)	5.39 (0.93)	5.47 (0.98)	5.64 (0.97)	5.74 (1.00)	5.43 (0.97)	5.41 (0.96)
ICC	13.58%	13.19%	9.52%	8.61%	6.83%	5.69%	7.37%	7.14%
DIC	1858	1823	1759	1758	1751	1747	1739	1741

The variance parameters are the medians of 50,000 chains with a burn-in of 500.

Continue:

	Individual and Neighbourhood predictors		Cross-level interactions
	Hierarchical block 1	Hierarchical block 2	
	variance (SE)	variance (SE)	variance (SE)
Neighbourhood	0.61 (0.52)	0.68 (0.51)	0.54 (0.47)
MOR	2.11	2.20	2.01
Individual	5.99 (1.18)	5.90 (1.00)	6.05 (1.08)
ICC	6.19%	6.90%	5.42%
DIC	1728.038	1727.802	1722.471

In order to test whether these results are affected by the highly skewed distribution of the individual latent traits observed in Chapter Three and Chapter Four, a sensitivity analysis using multilevel latent class analysis is performed in MPLUS. Results are similar, and therefore only the multilevel continuous models are reported here. In addition, it is observed that in the fully-adjusted models, the individual distribution became more approximately Normal for both traits. This observation confirms the multilevel assumption of Normal distribution of the variances at the higher levels, which is conditional on the fixed effects.

Results from the multilevel mediation model

The models so far are traditional regression equations involving a single equation. No sense of causal ordering in terms of pathways has been imposed on the analysis so that each variable has been treated on an equal basis as a predictor of aggressive behaviour. The results of this overall-effects analysis indicate that, among the structural neighbourhood variables, only the availability of community resources significantly predicts levels of adolescent aggression over and above individual-level characteristics. As discussed previously, however, showing a direct relationship between the structural variables and individual aggression is not fundamental to establishing mediation. In these circumstances, the guidance in the literature is to explore potentially suppressed relationships or indirect effects (Shrout and Bolger, 2002, MacKinnon et al., 2000).[9] Consequently, this section undertakes an analysis to reveal potential hidden indirect effects between the distal structural neighbourhood conditions and adolescent aggressive behaviour. These causal pathways are imposed on the data by using the logical temporal order of the conceptual model, as regrettably there is no information on the adolescents over time.

Deprivation, physical social disorder, community resources, social cohesion and informal social control are all neighbourhood-level measures, so that all the hypotheses to be tested in this section require a 2-2-1 and a 2-1-1 mediation design. Therefore, the indirect effects of interest are estimated at the neighbourhood-level. To test the study hypotheses, both single-step and multiple step MSEM procedures are used on both scales of aggressive behaviour simultaneously.

Single-step MSEM model

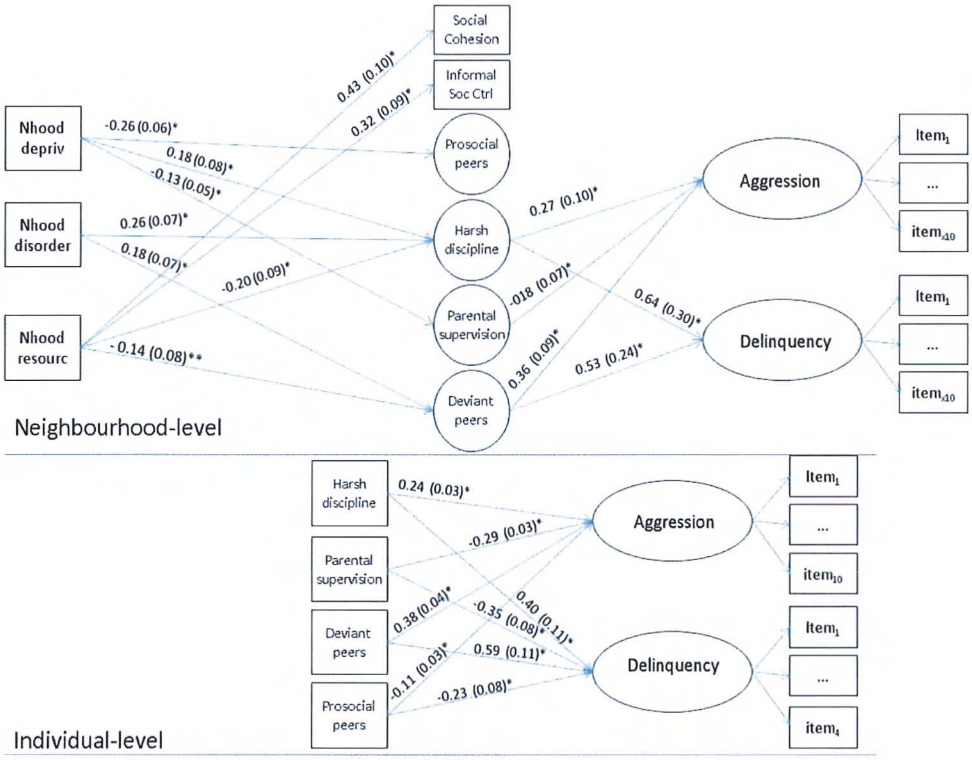
The first hypothesis to be evaluated is that structural neighbourhood conditions - deprivation, physical social disorder and community resources- are indirectly related to aggression/delinquency through their effects on the social processes within the neighbourhood, the quality of parenting and peer associations. The resultant single-step model presented in Figure 43 is estimated using the MPlus (Muthén and Muthén, 1998-2010) software and Appendix 4 provides the syntax. The values on the graph report both the individual and neighbourhood-level pathway standardized coefficients on the probit scale, and their corresponding

[9] Indeed, the results for Model F of the aggression scale already show evidence of such suppression, as the effect of community resources are suppressed before the inclusion of the effect of deviant peers.

standard errors. Although interest is focused on the neighbourhood-level, the figure also gives the results at the within-neighbourhood, individual-level to facilitate the comparison across the different levels of analysis. For easy reading, only paths and coefficients that are significant at the 10% level are displayed.

Adjusting by individual-level confounding factors, the MSEM analysis identifies the individual-level deviant peer associations as the greatest influence for both types of adolescent aggressive behaviour, followed by harsh discipline. In contrast, parental supervision and prosocial peers exert a very important protective role, particularly against delinquent behaviour. Furthermore, the analysis demonstrates that these relations also hold at the neighbourhood-level, with the exception of the effects of parental supervision on delinquency and prosocial peers, which are not found to be significant. Consistent with the results derived from the three-level Rasch model, neighbourhood social processes are not predictive of adolescent aggressive behaviour.

Focusing on the left, that is distal, side of the figure, it is found that structural conditions of neighbourhoods have a strong influence of the quality of parenting and on the type of friends adolescents associate with, while impacting not at all on the social processes within the neighbourhood. As can be seen, neither neighbourhood deprivation nor neighbourhood disorder is related to neighbourhood social cohesion or informal social control. However, an increase in the level of community resources is significantly associated with increases in the level of neighbourhood social processes, and simultaneously with decreases in the parental use of harsh discipline and association with deviant peers (although this relationship is only significant at the 10% level). In contrast, higher levels of neighbourhood disorder are positively associated with levels of harsh discipline and deviant peer influences, while higher levels of deprivation are associated with lower levels of parental supervision and prosocial peers. Consequently, structural neighbourhood factors exert their effect on adolescent aggressive behaviour indirectly by increasing the risk of poor parenting and higher deviant peer affiliations.



*p<0.05, **p<0.10

Figure 43 MSEM under a single-step mediation model with standardized coefficients

Table 46 provides the results of the estimated indirect effects for the significant pathways. The indirect effect of neighbourhood deprivation through harsh discipline and parental monitoring on aggression is significantly different from zero. Similarly, the indirect effect of disorder on both aggression and delinquency through harsh discipline is statistically significant, as is the indirect effect through deviant peers. Finally, the indirect effect of community resources on aggression via harsh discipline is also significant, but not through deviant peers. Consequently, the variable deviant peers is not on the causal chain between community resources and aggression, and therefore is not a suppressor factor as speculated from the results in Model F. According to the results of the MSEM model, deviant peers exert a negative confounding effect in such relationship, indicating the importance of controlling for the effect of this variable in future research. However, the significance of the indirect effects of the other variables indicates that structural neighbourhood conditions are important for adolescent aggressive behaviour given that, although they may not influence it directly (excepting of community resources), they affect processes which are found to be strongly related to aggressive behaviour.

Table 46 Indirect effects and 95% CI of structural neighbourhood conditions on aggression and delinquent aggressive behaviour through proximal individual variables

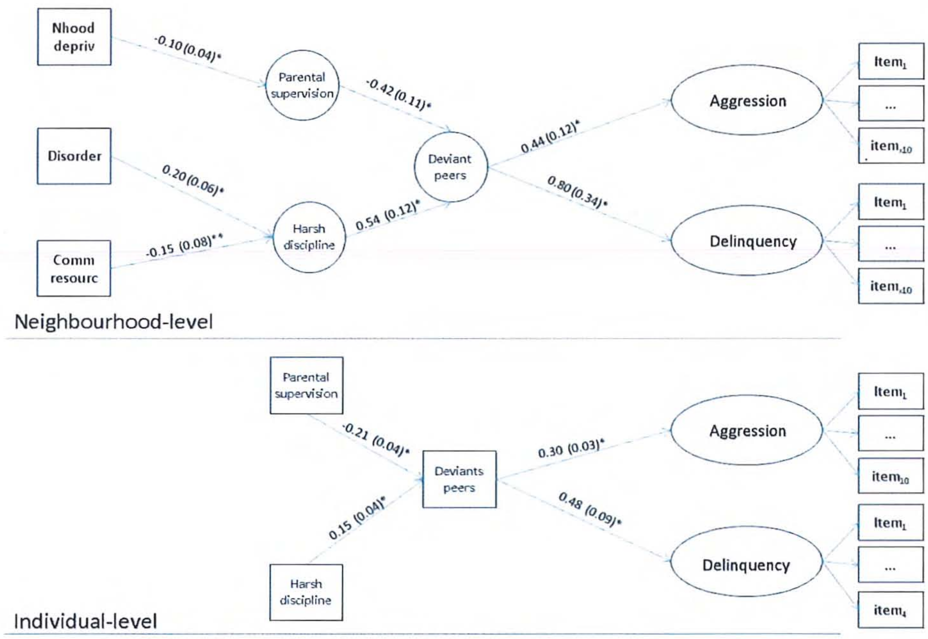
	Aggression		
	Harsh discipline	Parental supervision	Deviant peers
	Indirect effect (95% CI)	Indirect effect (95% CI)	Indirect effect (95% CI)
Neighbourhood deprivation	0.049 (0.003 - 0.114)	0.022 (0.003 - 0.054)	NS
Physical social disorder	0.069 (0.016 - 0.143)	NS	0.065 (0.014 - 0.132)
Community resources	-0.054 (-0.130 - -0.003)	NS	-0.050 (-0.121 - 0.004)
	Delinquency		
	Harsh discipline	Parental supervision	Deviant peers
	Indirect effect (95% CI)	Indirect effect (95% CI)	Indirect effect (95% CI)
Neighbourhood deprivation	0.116 (-0.003 - 0.301)	NS	NS
Physical social disorder	0.162 (0.010 - 0.374)	NS	0.094 (0.003 - 0.234)
Community resources	-0.127 (-0.334 - 0.003)	NS	-0.072 (-0.212 - 0.012)

NS= no significant path chains

Multiple-step mediation model

The final stage in the analysis is to use a multi-step mediational model to 'unpack' some of the causal chains linking neighbourhood structural characteristics to aggressive behaviour. As described by the 'Parenting practices, peer affiliations and neighbourhood social network model' of Chapter Two and by the conceptual model in Figure 33, the effects of structural neighbourhood conditions on aggressive behaviour may be transmitted through a set of steps representing intervening variables, rather than the one supposed by the single-step model. This theory is evaluated through a multiple-step mediation approach. Two hypotheses are evaluated: i) parenting practices serve as a mediator of the relationship between structural conditions and deviant peers; and ii) peer associations mediate the role of parental practices and adolescent aggressive behaviour. Again MPlus is used for this estimation and the syntax code is given in Appendix 2. Given that the single-step model finds little evidence for the importance of neighbourhood social processes and prosocial peers as mediating factors, they are not included in this multiple step model. Figure 44 presents the standardized path coefficients, showing only those paths that are significant at a level of 10%.

In general, the results reveal the importance of parenting practices and peer influences on adolescents. Deprived and disorganised neighbourhoods seem to exert an indirect effect on adolescent aggressive behaviour through disruptive parenting processes, thereby rendering adolescents more susceptible to deviant peer influences, which leads in turn to higher aggression and delinquency. Neighbourhoods with high availability of community resources seem to exert a protective indirect effect by being associated with quality parenting practices and quality of friends, which in turn reduces adolescent aggressive behaviour.



*p<0.05, **p<0.10

Figure 44 MSEM under a multiple-steps multiple mediation model with standardized coefficients

The first hypothesis to be evaluated is a 2-1-1 hypothesis, examining the mediated or indirect effect of neighbourhood structural conditions on deviant peers, that is transferred via parenting practices. The evidence of Figure 44 is that neighbourhoods significantly influence the quality of parenting, and that low parental supervision and high levels of harsh discipline increase adolescent affiliation with deviant peers. The estimated indirect effect (Table 47) of neighbourhood deprivation on deviant peer affiliations shows that this is transferred through parental supervision. This effect is statistically significant, with CIs that do not overlap zero on the probit scale. The indirect effect of neighbourhood disorder on deviant peer affiliations transferred via harsh discipline is also significant, but the indirect effect of community resources on deviant peers affiliations transferred via harsh discipline is not. In summary, it can be concluded that community resources do not exert an indirect influence on the deviant affiliations, but neighbourhood deprivation and disorder do.

Table 47 Indirect effects and 95% CI of structural neighbourhood conditions on deviant peers through parenting practices

	Deviant peers	
	Parental supervision	**Harsh Discipline**
	Indirect effect (95% CI)	**Indirect effect (95% CI)**
Neighbourhood deprivation	0.04 (0.01 - 0.09)	NS
Physical social disorder	NS	0.11 (0.04 - 0.20)
Community resources	NS	-0.08 (-0.18 - 0.004)

NS= no significant path chains

The second and last hypothesis involves a 1-1-1 hypothesis evaluating the mediating or indirect role of peer associations in the relationship between parental practices and adolescent aggressive behaviour. As illustrated in the individual- part of Figure 44, parenting practices are significantly associated with deviant peer influences. In addition, deviant peers are significantly related to both aggression and delinquency. The estimation of the indirect effects and confidence intervals are shown in Table 48. Parental supervision has a significant indirect effect on aggressive behaviour via deviant peers, while its effect on delinquency is also significant. In summary, parental supervision has a significant protective indirect effect on both aggressive behaviour scales. The indirect effects of parental harsh discipline through deviant peers on both forms of aggressive behaviours are also significant. These results support the mediation hypothesis; that there is a positive indirect effect of harsh supervision on both aggressive behaviour scales. Moreover, since the level of affiliation with deviant peers is a function of both the levels of neighbourhood structural conditions and how parents manage their adolescents, deviant peers stand as an important mediating factor, transferring both neighbourhood and family effects to adolescent aggressive behaviour.

Table 48 Indirect effects and 95% CI of parenting practices on aggression and delinquent behaviour through deviant peers

	Aggression	Delinquency
	Deviant peers	Deviant peers
	Indirect effect (95% CI)	Indirect effect (95% CI)
Parental supervision	-0.06 (-0.09 - -0.04)	-0.10 (-0.16 - -0.05)
Harsh discipline	0.04(0.02 - 0.07)	0.07 (0.03 - 0.12)

Conclusions

This chapter investigates the association between individual and neighbourhood characteristics on adolescent aggressive behaviour. In particular a conceptual model based on a logical temporal order of variables is developed and this guides the adjusted analysis and the elaboration and estimation of the pathways linking the characteristics of neighbourhoods to individual–level outcomes. These models are estimated and evaluated by integrating multilevel and structural equation modelling.

Adjusted results indicated that individual-level variables, such male gender, family antecedents of criminality, having witnessed or experienced violence as a victim, severe harsh discipline and frequent association with deviant peers, are all associated with higher odds on both aggressive behaviour scales. Parental monitoring and prosocial peer associations are associated with lower odds. Contrary to expectations derived from previous research, parental stress is not predictive of aggression or delinquency.

In regard of the neighbourhood predictors, it is found that, after adjustment by individual factors, the spatial concentration of adolescents who are victims of violence, and whose parents suffered stressful life events in the previous year, increases the likelihood of aggression, whereas the availability of community resources reduces it. This latter effect is only disclosed when the negative confounding effect of deviant peers is controlled for; consequently, these results highlight the importance of controlling for the effect of more proximal variables in future research.

Results from Chapter Four have demonstrated that neighbourhoods vary much in the log-odds of engaging in adolescent aggressive behaviour, and the results in this chapter from the three-level Rasch model suggest that this variation is largely accounted for by individual variables. The multilevel findings suggested that not only is most of the variation in adolescent aggressive behaviour occurring within the neighbourhood, but that most of the between-neighbourhood variation is due to the neighbourhood concentration of adolescents with similar characteristics. When these are controlled for, the neighbourhood-level variation is much diminished. However, there is evidence of significant cross-level interactions. Consequently, the effect of individual characteristics can be moderated by neighbourhood characteristics. For example, it is found that in deprived neighbourhoods harsh discipline has stronger effects on both types of aggressive behaviour. However, where deprivation is low, harsh discipline has little effect. Similarly, in low violent neighbourhoods, affiliations with deviant peers have little effect on aggression and on delinquency but a significantly larger effect in highly violent neighbourhoods. The analysis also revealed that the effect of having witnessed violence on aggression is non-significant in the neighbourhoods with high neighbourhood social control, while its effect on delinquency is stronger in high violent neighbourhoods. Such results suggest that neighbourhood conditions are important for aggressive behaviour, depending on the individual characteristics of adolescents.

Results from the multilevel mediation model support the ecological theory in the sense that there are significant inter-relationships of influences among different social settings on adolescent aggressive behaviour. With the exception of neighbourhood community resources, no structural neighbourhood condition shows a direct association with adolescent aggressive behaviour, however; several indirect effects are observed. According to the results, structural conditions of the neighbourhood influence adolescent behaviour because they affect how parents control their children and the quality of peers that they socialise with. Consequently, one important implication of this result is that research limited to the study of the direct effects is missing important information about the mechanisms through which structural neighbourhood conditions influence adolescent aggressive behaviour.

According to the model estimates, the most important factors to transmit the effect of the structural neighbourhood conditions are deviant peers and harsh discipline, which are found to be highly related to the odds of both aggression and delinquency. Specifically, the MSEM results demonstrate that lack of community resources and higher levels of disorder exert an effect on the likelihood of adolescent aggressive behaviour through two mechanisms that work in the same direction, by increasing inconsistent and severe parenting practices, which then increase the likelihood of aggressive behaviour, while simultaneously increasing associations with deviant peers. Neighbourhood deprivation also exerts a positive influence on aggressive behaviour by increasing levels of harsh parental discipline and low supervision. In addition to these indirect effects, it is also found that deviant peers transfer the effects of both structural conditions and parenting practices. The analysis strongly indicates that three different indirect effects operate through deviant peers. One of them refers to the protective effect exerted by parental monitoring, and the others to the perverse effects exerted by harsh discipline and neighbourhood disorder.

In conclusion, residing in disadvantaged neighbourhoods does have adverse consequences on adolescent aggressive behaviour, mainly because the lack of effective strategies of parenting which allows affiliations with deviant peers. Thus, family and peer influences are revealed to be important influences of adolescent behaviour. Therefore, a more efficient intervention for reduction of adolescent aggressive behaviour should target areas with high odds of aggressive behaviour and focus not only on improving community resources and reducing adolescent experiences of violence of parental stress, but, more importantly on the control of adolescent peer groups, lack of parental monitoring and inconsistent discipline.

Chapter 7. Discussion and general conclusions

This final chapter aims to summarize the more important findings, compare them with previous literature and discuss their explanatory meaning. In addition, the limitations encountered during the research process are outlined, and these provide the basis for recommendations for future research. Finally, the implications of the findings for the design of effective neighbourhood intervention programs are discussed.

The present research has two main purposes. First, to advance the theoretical reasoning and methodological techniques to capture more fully individual and neighbourhood characteristics. Second, to look for explanations of neighbourhood effects on adolescent aggressive behaviour in a Latin American context. The review of Chapter Two considered the challenges of bringing together two systems that have mainly been investigated separately: individual and neighbourhood. In particular, the review highlighted the methodological problems in relation to the measurement of individual aggressive behaviour, neighbourhood conditions, as well as the creation of an integrated theoretical framework. This not only combines individual and neighbourhood theories of aggressive behaviour but also aids in the exploration of the complex interplays of moderating and mediating relationships that potentially operate at different levels.

To meet these challenges, the thesis has integrated techniques and knowledge from a number of different disciplines –geography, epidemiology, education, psychology, criminology and statistics. A conceptual framework is developed which specifies the logical order of the effect of the variables on adolescent aggressive behaviour and considers processes operating at more than one level. This underpins a novel technical analysis based on multilevel modelling, item response theory, ecometrics, psychometrics and MSEM that generates more precise estimates of the effects of individual and neighbourhood variables on adolescent aggressive behaviour, and allows the evaluation of hypotheses relating to the mechanisms by which neighbourhoods potentially determine adolescent aggressive behaviour.

The multilevel Rasch model identified two separate constructs of adolescent aggressive behaviour: aggression and delinquency. Although such scales are quite highly correlated at both the individual and neighbourhood level, they do not share the same individual and neighbourhood predictors. As such, they should be analysed and interpreted as different forms of aggressive behaviour for which separate aggressive behaviour theories may be developed.

After controlling for measurement error, the analysis reveals that in Medellin the probability of a typical adolescent engaging in aggression is 7.0% and in delinquency 0.3%. There is also a significant variation for both forms of aggressive behaviour at the neighbourhood-level which accounts for some 7.0% of the aggression and 14% of the delinquency scale. Although this research uses a set of different aggression items to measure the two aggressive behaviour scales, the results can be compared with those reported by the two studies carried out by the Project on Human Development in Chicago Neighbourhoods (PHDCN), the only two previous ones that have used this sophisticated methodology. The study of Chuang *et al.* (2005) found an overall probability of endorsement on an aggression item scale of 26% and a much lower probability of 4% for a delinquency set of items. In their study there was also a statistically significant variation in the log-odds of an affirmative response between-child and between-neighbourhoods, with 2% and 3.4% of the variation of the aggression and delinquency scale at the neighbourhood-level. The second study carried out by Raudenbush *et al.* (2003) reported a probability of engaging in violent crime of 14% and in property crime of 2.6%. The authors found statistically significant variation between tracts for violent crime (7%) but not for property crime. These results and the present research confirm the observation made by several studies of aggressive behaviour, including two Colombian ones (Duque et al., 2003, Duque and Klevens, 2000, Farrington, 1995, Farrington and West, 1993, Farrington et al., 2001) that the probability adolescents engage in the more aggressive acts (named delinquency or violent crime) is smaller than the probability of engaging in the less severe. These studies, as does this one, confirm the greater importance of neighbourhood variation for the more severe behaviours.

The Rasch-based approach allows the evaluation of the psychometric properties of the individual and neighbourhood aggressive behaviour scales. In particular, it permits to measure the reliability of the scale to discriminate between adolescents within a neighbourhood as well as to detect differences between neighbourhoods. The results show that the reliability is greater for the aggression scale than for delinquency. For adolescents within neighbourhoods, the average reliability for the aggression and delinquency scale is 0.71 and 0.21 respectively. For neighbourhoods, the corresponding average reliabilities are 0.94 and 0.19 respectively. These reliabilities suggest that it is possible to distinguish the general level of aggression among individual and neighbourhoods with high reliability, but that this is more problematic for the general levels of delinquency. Such reliabilities are also encountered by the two Chicago studies. Raudenbush *et al.* (2003) estimated a reliability at the adolescent-level for the violent crime scale of 0.65 and for the property crime scale a value of 0.50. At the tract-level, the reliability was 0.42 for violent crime while zero for property crime. Similarly, in the study of Cheong and *et al.* (2005), the average reliability measures at the children-level for aggression and delinquency were 0.83 and 0.60, respectively. At the neighbourhood-level, the corresponding average reliabilities were 0.38 and 0.36. According to several authors (Raudenbush et al., 2003, Chuang et al., 2005, Raudenbush and Sampson, 1999b, Kamata and Cheong, 2007), the main factors affecting the individual and neighbourhood reliabilities are a small number of individuals per neighbourhoods (25 is the required rule of thumb), a small between-neighbourhood variation, a small number of neighbourhoods and a small number of items that make up the scale. In the present research, the low average reliability values for the delinquency scale can be attributed not only to the small number of adolescents in some neighbourhoods, but also to the low number of items that make up this scale (four items), and to their high item severities. Even with these low neighbourhood-level reliabilities, the two Chicago studies as well as the present research are able to detect significant effects of predictor variables at the individual and neighbourhood level (results described in Chapter Six).

An important methodological consideration described in Chapter Two is the need to measure properly neighbourhood constructs that tap the several conditions hypothesized to affect adolescent behaviour. In particular, valid measures of neighbourhood social processes are required. In the present study, this information is obtained through several sources of data including both survey and administrative routine data. A coherent sequence of steps is developed by the present researcher to produce valid neighbourhood measures. This involves using a range of different methodologies such as multilevel factor analysis, ecometrics, multilevel spatial multiple membership models, multilevel latent class analysis, geographical information systems (GIS) and empirical Bayes approaches. The more important advantages of this model-based approach are:

1) It allows the exploration of the nature of the data at the neighbourhood-level, and therefore, focuses on obtaining uni-dimensional scales operating specifically at that level, while partialling out household variation.
2) It can be applied to whatever scale of measurement used to define the input variables, be it continuous or categorical, and thereby avoids elements of subjectivity in the definition of the scales and on the choice of cut-off points.
3) It takes into account the potential of spatial relationships between the neighbourhood measures and includes such effects in the final neighbourhood estimates.
4) For variables derived from survey data, these methods allow the assessment of the ecometric properties of the resultant neighbourhood

scales which provide valuable information about their reliability and validity.

5) The resultant neighbourhood measures are precision-weighted estimates which exploit fully the available data, with the estimates for otherwise relatively poorly- estimated neighbourhoods borrowing strength from those that are more reliably estimated.

A total of seven neighbourhood variables describing structural characteristics of the neighbourhood are developed. They are labelled: deprivation, physical and social disorder; perceived availability of institutional resources; access to parks/recreational facilities; access to security/policing; access to social/cultural facilities and homicide rate. In addition, two neighbourhood variables describing the social processes within the neighbourhood are derived: informal social control and social cohesion.

Results from the multilevel exploratory factor analysis of the structural neighbourhood conditions confirm Muthén's (1994) observation that the number of factors at the neighbourhood-level are fewer than the number of factors at the household-level. Thus, for the set of variables measuring the structural characteristics, only one construct is found to be distinguishable at the neighbourhood-level (neighbourhood deprivation) while three can be recognised at the household-level (concentrated disadvantage, non-professional families and residential instability). This differing factor structure at the household and neighbourhood-level is not consistent with the available literature, which in general uses the same set of input variables as here, although as aggregated measures, to create two structural neighbourhood conditions of deprivation and mobility. For example, Cerda *et al.* (2008) using variables derived from the *'Survey of Dimension and distribution of different kinds of violence'* undertaken in Medellin in *2003* created the two structural neighbourhood constructs. This study factor analyzed three aggregate measures of socioeconomic status (neighbourhood official social class, proportion of households in the two lowest social classes, and proportion of residents on public assistance), as well as two aggregated survey responses of residential stability ('proportion of respondents in a neighbourhood who lived in the same house for five years or more' and the 'proportion who own their own home'). The measures of social class loaded strongly onto the concentrated disadvantaged factor, while the two measures of residential stability loaded strongly and positively onto another factor. The discrepancy between the results of the present research with those of Cerda *et al.* (2008) requires further investigation; however, it may simply reflect the inadequacy of using neighbourhood aggregates. As argued by Gauvin *et al.* (2005), aggregating survey data may lead to mistaken conclusions about the factors operating at the neighbourhood-level, where the identified neighbourhood constructs may reflect individual/household traits rather than real neighbourhood conditions. According to the current Medellin results, the residential instability construct seems to be operating only at the household-level. Further research is needed to explore which additional set of variables can be better indicators of residential instability at the neighbourhood-level. However, the present study finds that there is not a distinctive construct of differential mobility at the neighbourhood-level when the analysis is based on the usual data, but an improved methodology is deployed that does not erroneously conflate household and neighbourhood variation.

Results from the ecometric models show that all the neighbourhood constructs can be measured with high reliability, with neighbourhood reliabilities ranging from 0.86 to 0.98 and the proportion of variation at the neighbourhood ranging from 0.13 to 0.47. There are three previous applications of the ecometric approach; they report similar reliabilities. By using community survey data from the PHDCN for 8,782 respondents nested in 343 neighbourhoods, Raudenbush and Sampson (1999b) developed neighbourhood measures to represent: social disorder, perceived violence, social cohesion, social control and neighbourhood decline. The resultant scale reliabilities ranged from 0.74 to 0.89 and the respective proportion of neighbourhood variance ranged from 0.13 to 0.39. Similarly, Fone *et al.* (2006) analysed data from the Caerphilly Health and Social Needs Study where the responses from 11,078 participants living in 325 UK census enumeration districts are used to capture different dimensions of neighbourhood cohesion. Two constructs labelled 'neighbourhood belonging' and 'social cohesion' are identified, with reliabilities ranging from 0.30 to 0.70 and the respective proportion of neighbourhood variance from 0.010 to 0.064; these low values for the between variance, perhaps suggesting that enumeration districts are not very meaningful as neighbourhoods. Finally, Gauvin *et al.* (2005) established the reliability and validity of neighbourhood-level measures of active living potential (activity-friendliness, safety and density of destinations) with reliabilities ranging from 0.76 to 0.83 and proportions of neighbourhood variance ranging from 0.33 to 0.35. All these studies, along with the present one, confirm the feasibility of measuring reliable and valid neighbourhood constructs by using individual data that are explicitly modelled and not simply aggregated. This study contributes to this embryonic but growing literature, concerned with the proper measurement of neighbourhood-level factors, by integrating different methodologies and creating a novel sequence of steps that can be replicated in future studies to create and assess uni-dimensional, valid and reliable neighbourhood constructs. Importantly this methodology has an exploratory and confirmatory phase so that it guards against the 'Garbage In, Garbage Out' description of traditional factor analysis (Williams, 1971).

Medellin shows certain 'hot-spots' of problematic structural and social neighbourhood conditions. A visual examination of the spatial distribution of the neighbourhood scores shows, for example, that neighbourhoods with high levels of deprivation and physical and social disorder are located in the north of the city, in particular, along the northern periphery. These areas also show the highest levels of both informal social control and social cohesion. Contrary to the observation of the social disorder theory and broken window theory, whereby highly disadvantaged neighbourhoods are characterised as socially disorganized, neighbourhood disadvantage in Medellin is *positively* correlated with neighbourhood social organization. This same pattern is reported by Cerda *et al.* (2008) in their aggregate analysis of the city. They argue that the observed pattern is different from the classic Chicago results because disadvantaged, socially organized communities are characterized by migrant populations from rural areas who are often forced to build illegal precarious houses on previously unoccupied land. These illegal settlements used to lack basic amenities such as energy, running water, sewerage, education and health care, which have to be demanded from the local government. Social organization is thus a necessary requirement to achieve these basic necessities of urban life. Moreover, these disadvantaged communities have a particular physical layout that strengthens social bonds. According to Cerda *et al.* (2008), such neighbourhoods tend to have high population densities, properties with shared common frontage and less open common space, which in turn promote higher socialization and organization among neighbours. Such results reflect the importance of context and the need for place-specific empirical work as not all structures and processes necessarily conform to the findings of more highly-researched, economically-developed countries.

The empirical evidence derived from the multilevel models in Chapter Six confirms the importance of the individual and neighbourhood-level characteristics in predicting adolescent aggressive behaviour. Despite the high correlation between the two forms of adolescent aggressive behaviour at both individual and neighbourhood-level, they showed distinctive associations with individual and neighbourhood predictors. Aggression is more strongly related to older male adolescents, with antecedents of family criminality, who have witnessed or been a victim of violence, with parents using harsh punishment strategies, with poor peer relations and neighbourhood effects relating to the concentration of resources, victims of violence and families experiencing stressful life events. Delinquency is related to males, not be studying, with antecedents of family criminality, who have witnessed or been a victim of violence, whose parents use harsh discipline strategies and who have deviant peer associations. The differential association with the predictors defined at the two scales challenges the assumption of uni-dimensionality which may be anticipated by the high correlation between the scales. This finding confirms Cheong and Raudenbush (2000) and Raudenbush *et al.* (2003) who highlight the necessity of assessing dimensionality, even in cases when the scales are highly correlated. It also confirms their argument that high correlations are not enough to warrant the presence of a single dimension. Instead, a differential association with individual and contextual covariates is required to reject such uni-dimensionality.

The association of the two aggressive behaviour scales with the listed covariates is highly consistent with the literature across settings. As noted by different authors, aggression significantly increases from middle childhood through the late teenage years, particularly for boys (Baillargeon et al., 2007, Broidy et al., 2003). Such gender differences have been explained by the greater 'risk personality' of boys, impulsivity and the increased probability of attention problems (Herrera and McCloskey, 2001). Conversely, girls are seen as having different manifestations of problematic behaviour such as depression, eating disorders, early pregnancy, alcohol and drug abuse (Broidy et al., 2003). Consequently, their manifestation of aggressive behaviour as measured in the present study is significantly and substantively lower.

Many studies have also documented the broad range of negative consequences for adolescent behaviour of exposure to violence, both as a victim and as a witness (Buka et al., 2001, Lynch, 2003). The results of this research show that adolescents who have witnessed or experienced violence have higher risk of both aggression and delinquency. Several researchers have found the same results. Richters and Martinez (1993) reported that children living in violent neighbourhoods or unstable families are more likely to display problem behaviours. These results lend support to the contagion theory described in Chapter Two, in which high levels of exposure to violence at home or in the neighbourhood/school may generate feelings of anger, frustration, lack of control over stressful events as well as aggression and hostile behaviour as a protective measure. Researchers have argued that adolescents who persistently witness violence, learn and accept aggressive behaviour as a standard problem-solving skill. As Sampson and Wilson (2005) have noted, in high violent environments young people are more likely to see violence as a way of life.

In addition, the results confirm the increased risk of aggression and delinquency generated by antecedents of family criminality. According to the model estimates (and controlling for other factors), adolescents with antecedents of family criminality have twice the risk of aggression and seven times the risk of delinquency when compared with adolescents without such antecedents. Farrington *et al.* (2001) report similar relationships. According to the authors, arrests of close relatives (brothers, sisters, fathers, mothers, uncles, aunts, grandfathers and grandmothers) strongly predict young delinquency. In particular, the arrest of the father is the strongest predictor. This result may suggest that adolescents learn and repeat aggressive behaviour from their own relatives. A potential explanation of this continuity of aggressive behaviour across generations is the potential of intergenerational continuities of exposure to multiple risk factors. As Farrington *et al.* (2001) argue, it is possible that each successive generation continues living constrained life conditions such as disrupted families, single and teenage parenting, and living in the most deprived neighbourhoods.

The present research found greater risk of aggression and delinquency among maltreated adolescents. According to the literature, substantial maltreatment that begins and persists into adolescence is significantly related not only to aggressive behaviour but also to other adverse outcomes, such as delinquency, alcohol and drug abuse, teen pregnancy and dropping out of school. According to a study undertaken in Australia (Fagan and Najman, 2003), several situations may lead parents to manage their children by harsh and coercive means. Families with younger, unmarried and uneducated mothers and with numerous children face stressful situations on a daily basis. This reduces their ability to educate and provide proper discipline for their children and to solve family conflicts appropriately. This ineffective behaviour may alter the way an adolescent processes social information and social cues, increasing the probability of developing aggressive behaviour.

As expected, adolescents with deviant peer influences manifest higher propensity for both aggression and delinquency. This association is also reported by Keenan *et al.* (1995) and by Heinze *et al.* (2004) where deviant peer groups reinforce aggressive behaviour by ways of support and motivation. These results also therefore support the contagion theory described in Chapter Two. The protective role of prosocial peers is significant for adolescent aggression, but not for adolescent delinquency. Failing to find statistically significant differences may be a result of the small number of adolescents with delinquency problems that have prosocial peers. However, the results for aggression are in agreement with conclusions from previous studies (Abbott et al., 1998, Fredricks and Eccles, 2005). Strong bonding with prosocial peers makes adolescents less willing to engage in aggressive behaviour through the development of an activity-based culture with shared conventional norms and values, which may in turn, influence individual members. Such prosocial groups may promote participation in extracurricular activities, which are known to reduce the probability of aggressive behaviour. They are also known to promote academic success and participation in sports which again may reduce the risk of aggressive behaviour. These results are of particular interest, given that most studies focus on investigating the effect of factors that predispose adolescents to aggressive behaviour, and much less on factors that provide protection in the presence of risk (Lahey et al., 2003). These findings provide evidence for the importance of protective processes and provide the basis for the design of more effective interventions.

In terms of neighbourhood-level factors, this study finds that density of community resources (such as parks, places for practicing sports, open spaces, social rooms and communal centres) is a significant predictor of adolescent aggression, although not of delinquency, even after controlling for individual characteristics. Diverse institutional resources can stimulate the participation in local organizations as well as provide open spaces for interaction with others peers with prosocial behaviours. A study undertaken by Molnar *et al.* (2008) also found this result. Indeed, they found a differential protective effect for neighbourhood resources on aggression, but not for delinquency, in adolescents. These results may suggest that the influence of neighbourhood resources on the more severe types of aggressive behaviour may be operating though other indicators such as the quality, quantity and diversity of such neighbourhood resources rather than their presence/ absence in the community. This issue requires further investigation with more detailed neighbourhood resources data, which also examines the differing adolescent engagement and use of these resources.

The Medellin study shows the perverse effects of neighbourhood levels of being victims of violence and of families experiencing stressful life events. Prior studies have not examined this type of contextual effect on aggressive behaviour. However, the results of the present research indicate that individual aggression responds to the exogenous characteristics of the local population. One plausible explanation may be that in these neighbourhoods, adolescents are more likely to engage with individuals who, due to their experiences as victims or stressed family life, have developed feelings of angry, frustration and lack of hope in the future, which in turn lead them to react with anger, and thus engage in aggressive behaviour as a defensive position against future situations.

Taking together, the set of individual and neighbourhood-level predictors explain 20% of the total variation of the aggression scale and 19% of the delinquency scale. Similar results are reported by Romano *et al.* (2005) when identifying individual, family, and neighbourhood correlates of childhood physical aggression in Canadian neighbourhoods. According to the authors, the total variation explained by the three-level model is 28%. These results indicate the need to explore a wider range of predictors that better explain the individual variation of adolescent aggressive behaviour. In the Medellin study when the set of individual demographic characteristics are included in the non-interaction, non-mediation model, the observed neighbourhood variation is estimated to be zero. This finding suggests that the differences in aggression and delinquency observed between neighbourhoods are mainly explained by clustering of similar types of adolescents and families in certain neighbourhoods rather than by characteristics of the neighbourhood itself. As described in Chapter Six, it is noticeable that most of the individual-level predictors are distributed non-randomly across neighbourhoods, and therefore, this result is to be expected. In addition, this result is consistent with the literature presented in Chapter Two, which demonstrated that in general the contextual variance of adolescent aggressive behaviour is small.

Nonetheless, as Raudenbush and Willms (1995) argue, the absence of significant variation at the neighbourhood level does not justify the conclusion that multilevel analysis is not needed, nor that there is no need to consider the effects of neighbourhood constructs. These authors explain that an apparently small component of variation between neighbourhoods can arise from the co-variation between individual-level predictors and neighbourhood-level variables. Therefore, cross-level interactions with moderated relations, whereby only particular types of adolescents are affected by neighbourhood conditions, may help to explain why neighbourhood effects are manifest in adolescent-level variation rather than as neighbourhood-level variation.

The present research finds evidence to support Raudenbush and Willms' (1995) argument. The exploration of cross-level interactions indicates that, even with zero proportion of neighbourhood-variance, the impact of some of the individual-level explanatory variables on both types of adolescent aggressive behaviour varies significantly across Medellin neighbourhoods. In particular, the effects of witnessed violence, harsh discipline, association with deviant and prosocial peers depend upon the characteristics of neighbourhoods. Given that there were not initial detailed hypotheses about specific cross-level interactions, the present researcher evaluated all of the individual/family variables and their cross-level interactions. This undoubtedly runs the risk of finding spurious significant results when such a large number of hypotheses are tested. This is mitigated somewhat by the similarity in the results for the two scales, their coherence (discussed below) and their face validity. However, the conclusions derived from this part of the analysis require confirmation from further studies.

In summary, the interactions indicate that the impact of witnessed violence, harsh discipline and deviant peers in adolescent aggression is much more substantial in communities with higher levels of structural neighbourhood adversities –such as deprivation and homicide– and low levels of neighbourhood social processes –social cohesion and informal control. Moreover the attenuating impact of prosocial peers on aggression is only pronounced in neighbourhoods with low social cohesion. These results suggest that adolescents living in disadvantaged and dangerous neighbourhoods, lacking in positive social processes, may be more exposed to violence, inconsistent parenting practices and deviant peers which therefore increase their probability of both aggression and delinquency. These results are coherent and compatible with previous work. Molnar *et al.* (2008) reported that in neighbourhoods with high collective efficacy, the protective effect of family support, presence of prosocial peers and availability of supportive non-parental on aggressive and delinquent behaviour is strengthened. Similarly, in neighbourhoods with high community resources, association with prosocial peers is especially protective against aggressive behaviour. Hoffmann (2003) also finds that the effects of stressful life events on adolescent delinquency are more consequential in communities suffering from high rates of male joblessness. Similarly, Rankin and Quane (2002) show that neighbourhood social organization moderates the effect of parenting on problematic behaviour. They find that in neighbourhoods with high collective efficacy, the protective effect of monitoring on adolescent problem behaviour is lower in comparison with its effect in neighbourhoods with low collective efficacy. Taking together, the results from the literature and from the present research suggest that, although there are not significant main effects for some of the neighbourhood conditions, they can be important in cases where other individual conditions are present.

A deeper investigation of the indirect impacts of neighbourhood conditions on adolescent aggressive behaviour further amplified and refined the previous findings. Results derived from the single-step multilevel SEM show that the availability of institutional resources not only directly reduces adolescents aggression, but also has an indirect effect by providing means of healthy socialization among families, which appears to reduce parental stress, increase better parental management practices and reduces association with deviant peers, which in turn reduce both aggressive and delinquent behaviour. This result suggests that good institutional resources provide spaces for organized activities where families can share and spend time, thereby structuring time and observing each other. Within these spaces, parents are more likely to form networks that enhance their direct monitoring and supervision of activities which may evolve into less aggressive behaviour. Other studies report the same results and demonstrate how community resources provide social contexts for the creation and maintenance of social bonds among residents, as well as promoting the sharing of common values and goals and their physical and socio-emotional wellbeing (Leventhal and Brooks-Gunn, 2000). Peterson *et al.* (2000) also argue that weak community resources lead to social isolation or lack of contact with individuals and institutions that represent conventional societies, which in turn lead to fewer conventional role models as well as fewer formal and informal mechanisms for supporting good behaviour.

The single-step multilevel SEM model also indicates that although neighbourhood disadvantage and disorder do not directly affect adolescent aggressive behaviour, they indirectly influence the way parents manage adolescents and the quality of peers that they come into contact with. According to the model results, parents in deprived and disorganized neighbourhoods exert less supervision and harsher parenting practices. These environments tend to have high concentrations of deviant peers, which also induce aggressive behaviour. In an effort to explain similar relationships, Rayne and Quane (2002) argue that parents in less deprived neighbourhoods seem to set clearer and better defined rules for their children and closely supervise their activities, while promoting prosocial adjustment and reducing levels of aggressive behaviour, compared to parents residing in more disadvantaged neighbourhoods. Moreover, parents living in deprived areas may have less time for parental involvement with adolescents due to their difficult economic and family circumstances, such as single-parenting, extra-hours of work, and low income. In addition, other authors (Hoffmann, 2006, Lynch, 2003) argue that poor and disorganized neighbourhoods may discourage both children and adolescents from adhering to conventional norms and produce feelings of hopelessness and socially unacceptable behaviours. As adolescents grow older, they tend to spend more time out of the home and be more influenced by the neighbourhood and prevailing antisocial models of living there. Consequently, children residing in disadvantaged communities have a higher probability of both exposure and affiliation with deviant peers than do children living in more affluent neighbourhoods (Brody et al., 2001, Eamon, 2002, Leventhal and Brooks-Gunn, 2000).

The consistency of the findings of the present study with those in the literature (Chung and Steinberg, 2006, Cattarello, 2000, Kohen et al., 2008, Rankin and Quane, 2002) is of great importance, since this confirms that the individualised risk-factor approach, which only considers overall and direct effects, involves an oversimplification of the processes involved. This study stresses the need to move beyond the 'black box' view that currently dominates neighbourhood literature towards the exploration of the underlying mechanisms linking neighbourhoods and adolescent behaviour. The implication of these findings is that neighbourhoods are important development contexts, and as such are potential targets for interventions designed to prevent and control adolescent aggressive behaviour. However, measures enhancing parenting practices and quality of peer associations would be more effective than only enhancing the physical and social conditions of the neighbourhood. But, additional consideration should be given to the protective influences of community resources.

In an attempt to evaluate the 'Parenting practices, peer affiliations and neighbourhood social network model' outlined in Chapter Two, this study performs a multiple step multiple mediational analysis that 'unpacks' multiple pathways in the relationship between neighbourhood conditions and adolescent aggressive behaviour. The results from this analysis provide strong empirical evidence to support the model. The analysis shows that adolescents who live in disadvantaged and disorganized neighbourhoods with lack of resources are more likely to have parents with inadequate coping skills who cannot provide them with a good home environment, manage neighbourhood risks and increase positive opportunities for adolescent well-being such as participation in sports or social organizations. These kinds of parents are more likely to use harsher and more punitive styles of discipline, and also be less able to monitor their children's activities outside the home environment, which increases their risk of associating with delinquent peers which in turn increases their potential for aggression and delinquency. These processes are all consistent with current literature of the presence of not only one link towards aggressive behaviour, but of a series of different pathways involving several different links.

This study is not without limitations. First, the data are based on a cross-sectional survey and therefore it is not possible to determine whether the associations observed are causal, as there is no way of establishing temporal precedence. In particular, results derived from the multilevel SEM analysis should be interpreted with caution, as there is no watertight way to rule out reverse causality (Lahey et al., 2003). Thus, for example, data from a cross-sectional design cannot adjudicate whether adolescents are more aggressive because their parents are more punitive, or alternatively, parents are more punitive because adolescents are more aggressive. Similarly, it is difficult to state that disadvantaged neighbourhoods lead parents to use harsher discipline strategies and generate delinquent peers or whether such people are more likely to move into deprived neighbourhoods. An important step forward for the present study would be to extend the analysis using longitudinal data. This study design has the advantage of allowing explicit modelling of the directions of causality hypothesized in this research, and thus to specify correctly the temporal relationship between neighbourhood characteristics and adolescent aggressive behaviour. In terms of modelling this can be accomplished by adding another level to the model so that the low level becomes occasion or time of measurement. This specification can handle time varying and time invariant predictors. The movement of adolescents between neighbourhoods can in principle, be handled by non-hierarchical multilevel models (Næss and Leyland, 2010).

The data used for defining neighbourhood constructs was collected in 2007, and there was no accounting for potential changes in neighbourhood conditions across years. Consequently, many of the observed relationships could reflect the effects of prior neighbourhood contexts. In this sense, the associations between current neighbourhood and aggressive behaviour could be conservative estimates of the cumulated effect of diverse neighbourhood conditions. As explained by Sampson (2006), neighbourhood exposures may have an important cumulative role on childhood stressors, which in turn may influence later adolescent behaviour in a life course sequence.

The neighbourhood definition used in this research is based on that derived by the city government for administrate purposes. Consequently, these areas may not represent the individual perception of neighbourhood, nor the place where social interactions are built. This is an important area for future research, whereby neighbourhoods are defined to respect local experience and to capture the ecological setting whereby social interactions and subjective meanings are developed and experienced.

The final, and probably the most frequently mentioned limitation of neighbourhood research, is the effect of selection bias. It is known that certain types of neighbourhoods attract or repel particular types of residents, and thus families are not randomly distributed. On the contrary, the choice or lack of choice, of which neighbourhood to live in is partly influenced by observable and unobservable family and individual characteristics, like education, income, and race/ethnicity, which may also influence children's behaviour (Peeples and Loeber, 1994). The methodology that is used in this thesis cannot isolate observable neighbourhood effects from the effects of unobservable individual-level characteristics that may be associated with neighbourhood characteristics. Such bias could result in the overestimation of the effects of neighbourhood by miss attributing effects that are purely related to the individual characteristics. However, in the present research this problem was at some extent minimized by controlling for the effect of observed individual and family characteristics that are highly related to the odds of adolescent aggressive behaviour, and by the development of a pathway model that specified variables in an explicit manner. The 'split sample' design, whereby neighbourhood data is obtained from a different sample than the adolescent survey, is used specifically to counter 'same source' bias. This may have resulted from correlated measurement error in the neighbourhood- level and individual-level variables if the data are derived from the same source (Diez-Roux, 2007).

Despite all these limitations, the present research provides important evidence about the presence of both compositional and contextual effects, about their inter-relationships to shape adolescent aggressive behaviour, and about the processes through which neighbourhoods constrain, enhance or modify individual level processes relating to adolescent aggressive behaviour. In general, the present study confirms the strong overall effect of the most proximal factors on adolescent aggressive behaviour and the distal or indirect effect exerted by neighbourhood conditions. It also confirms that some of the individual conditions are the results of the neighbourhood where adolescents live, and also that the reverse is true, that some of the neighbourhood factors are the result of the characteristics of its residents. This finding is coherent with Macintyre *et al.* (2002) arguments that 'places make people' as well as 'people make places'.

The present study shows that neighbourhoods exert an important influence on adolescent behaviour, which is mainly transmitted through families and the quality of friends present within the community. From a policy perspective, the findings indicate that interventions oriented to reduce adolescent aggressive behaviour may be more effective if they target the adolescents and their families in the identified high-risk neighbourhoods. Specifically, the results suggest that it is possible to prevent the negative effects of neighbourhood conditions if parenting practices are effective and quality of relationships are available within the neighbourhood. Consequently, parenting training on contingent, consistent and non-violent handling of adolescent behaviour could be effective means for preventive intervention. This may be accompanied by promoting successful relationships with peers who are committed to conventional and socially accepted behaviour. The research also highlights the importance of improving community resources for the Medellin neighbourhoods, in order to enhance its independent protective effect on adolescent aggressive behaviour, as well as to ameliorate stressful life events and youth victimization. Therefore, an integrated community intervention is required not only to improve the institutional resource provision for the neighbourhoods but also to enhance individual relationships that are necessary to reduce adolescent aggressive behaviour, and thus potentially prevent adult criminality.

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Appendix 1. Review of the association between neighbourhood characteristics and aggressive behaviour. October 2011

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
			North America			
Simcha-Fagan & Schwartz, 1986	United States Census data Community survey Caretakers' Quest Self-reported Quest Police registers 12 neighbourhoods Adolescents males 11.5 to 17.5 yrs old n=553 Cross-sectional	Neighbourhood	Delinquency (self-reported, officially recorded), severe self-reported delinquency (assault, robbery, burglary, grand larceny, arson)	**Neighbourhood Level** residential stability, SES, disorder-criminal subculture, organizational participation, **Individual Level** Family residential stability, family organizational participation, SES, age	Linear regression analyses	Neighbourhood characteristics significantly affected individual-level Delinquency
Peeples & Loeber 1994	United States Self-reported Quest Caretakers' Quest Teachers' Quest 7 schools Boys 13 yrs old n=506 cross-sectional	Schools	Delinquency seriousness (theft, carrying gun, breaking and entering, forced sex, aggravated assault, selling drugs)	**Neighbourhood Level** Underclass Index Neighbourhood classification **Individual Level** Hyperactivity, parental supervision outside activities, African American, poverty, welfare use, single-parent homes	Hierarchical multiple regression analyses	Residence in underclass neighbourhoods increase the risk of delinquency seriousness The delinquent behaviour of African American youths is similar to that of white youths when they do not live in underclass neighbourhoods

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
Simons, et al. 1996	United States Self-reported Quest Caretakers' Quest Adol 14.3 yrs old n=207 Transversal	Neighbourhoods	**Conduct problems, delinquency, substance abuse and aggressiveness**	**Neighbourhood Level** % single parent families, community disadvantage **Individual Level** Family SES, deviant peers, and quality of parenting	Structural equation modelling	For boys, community disadvantage is not directly related to conduct problems but has an indirect effect through its association with quality of parenting. For girls, single-parent households in the community had a direct effect
Boyle & Lipman 1998	Canada Self-reported Quest 1996 Census 5325 EAs parents: n=7799 children 4-11 yrs old n=11516 cross-sectional	Enumeration Areas (by postal code)	Child conduct problems; hyperactivity; emotional problems.	**Neighbourhood Level** % one parent families; % families below poverty; neighbourhood disadvtg **Individual Level** number of siblings; family status; family income; family SES;	Hierarchical linear model	Family-level measures more important than neighbourhood measures
Seidman et al. 1998	United States Self-reported Quest 1990 Census 203 census tracts Adolescents 10-17 n=754 cross-sectional	Census tracts	Antisocial behaviour (delinquency, alcohol use and negative involvement with peers)	**Neighbourhood Level** Structural neighbourhood risk: poverty-related hassles neighbourhood violence **Individual Level** Involvement in neighbourhood organizations and activities, neighbourhood cohesion, gender, race, family income, peer associations	ANCOVA	Youth living in moderate risk neighbourhoods reported more antisocial behaviour

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
Griffin et al. 1999	United States Children n=452	Neighbourhood	Interpersonal aggression, risk taking and externalizing behaviour problems	**Neighbourhood Level** Gang activity and delinquency **Individual Level** Parental Monitoring, friends' delinquency, anger control skills, gender and race	SEM Hierarchical linear Modelling	N'hood risk was associated with more aggression and this relationship was mediated partly by risk-taking Decrease in externalizing levels associated with more parental monitoring was significantly more pronounced when youths lived in neighbourhoods with more residential instability.
Wikstrom & Loeber 2000	United States Self-reported Quest Caretakers' Quest 90 Neighbourhoods adolescents 10-13 yrs old n=508 Longitudinal	Neighbourhood	Serious offending (theft, breaking and enterint, strong-arming, attack to seriously hurt or kill, forced sex or selling drugs), early onset (before age 13) and late onset (after age 12)	**Neighbourhood Level** Socioeconomic Disadvantage **Individual Level** Hyperactivity-impulsivity, attention problems, lack of guilt, poor supervision, low school motivation, peer delinquency, positive attitude towards antisocial behaviour	Linear regression	Neighbourhood socioeconomic context has any greater direct impact on the early onset of serious offending. Neighbourhood socioeconomic context has a direct impact on the late onset of offending for juveniles who scoring high on protective factors or who have a balanced mix or risk and protective factors
Cheong and Raudenbush 2000	United States Self-reported Quest 79 urban neighbourhoods 9-15 children N=2,177 Longitudinal	Neighbourhoods	Aggression and delinquency	**Neighbourhood-level** Concentrated disadvantage **Individual level** child age, child sex, primary caregiver ethnicity, and primary caregiver educational level	Three-level Rasch model	Concentrated disadvantage Significantly influence juvenile aggression and delinquency

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
Cattarello, 2000	United States Self-reported Quest 39 tracts Adolescents 14-15 yrs old n=1488 cross-sectional	Census tracts	Delinquency (marijuana's use)	**Neighbourhood Level** Social disorganization, mobility **Individual Level** Sex, age, race, family size, family structure, parent's education, social bonds, delinquent peers	Hierarchical linear modelling	The effect of social disorganization on delinquency is mediated fully by peer associations
Colder et al. 2000	United States Self-reported Quest Caretakers' Quest Teachers reports Children 10.3 yrs old n=732	Neighbourhoods	Aggression. (verbal aggression, physical fighting gang involvement	**Neighbourhood Level** perceived neighbourhood danger **Individual Level** Positive beliefs aggression, parenting practices and socioeconomic status	Structural equation modelling	Perceived neighbourhood danger was associated with strong positive beliefs about aggression, which in turn was associated with high levels of aggression
Lynam & et al. 2000	United States Self-reported Quest 90 neighbourhoods 13 years-old boys N=430	Neighbourhoods	Delinquency: status offences Vice, theft, violence and Total number of acts	**Neighbourhood level** Neighbourhood SES **Individual level** Race, family status,	Hierarchical regression modelling	Neighbourhood poverty has a Significant effect only on violent Crime. However, there are Significant cross-level Interactions
Beyers et al. 2001	United States Self-reported Quest Official registers 88 neighbourhoods Adolescents boys 13-19 yrs old n=420 Longitudinal	Census tract	Violent delinquency (attack with weapon, hurt someone or threat, forced sex, robbery) Repeated violence (>=2) Official serious delinquency (homicide, rape, robbery, aggravated assault, carjacking)	**Neighbourhood Level** Neighbourhood SES **Individual Level** Age, race, single parent status, family SES	Multivariate logistic regression models	Adolescents in high-SES neighbourhoods are less likely to commit acts of violent delinquency that their counterparts in low-SES neighbourhoods

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
Ludwig et al. 2001	United States Juvenile Arrest records Caretakers' Quest 5 census tracts 638 families Adolescents 12-15 yrs old n=1406 Randomized mobility experiment	Treatment groups	Arrests for criminal behaviour (violent crimes, property crimes, other crimes)	**Neighbourhood Level** Neighbourhood mobility to low-poverty areas **Individual Level** Sex, age, race, behaviour problems, learning problems, parent's SES, public housing parent's education, mother's age at youth' birth	Linear regression model	To move to lower poverty neighbourhoods reduces violent criminal behaviour by teens
Steward et al. 2002	United States 1990 Census Children's interview Caretakers' interview 259 neighbourhoods African American Youth 10-12 yrs old n=867 cross-sectional	Neighbourhoods (BGA)	Childhood violence behaviour (physical assault, threatening, bullying people, using a weapon)	**Neighbourhood Level** Neighbourhood violence, neighbourhood affluence **Individual Level** Family SES, corporal punishment, quality parenting, adopting a street code, peers associations, parental use of violence, gender, number of children per household, family structure	Linear regression model with robust standard error estimates	Children who grow up in affluent neighbourhoods are less likely to engage in violent behaviour

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
Rankin, Quane 2002	United States Interview 59 neighbourhoods African-American children 11-16 yrs old n=636 cross-sectional	Census tracts	Problem behaviour (delinquency and number of arrests) and prosocial competence	**Neighbourhood Level** Concentrated disadvantage, residential stability, collective efficacy **Individual Level** Parental monitoring, parental involvement, family rules, positive friends, age, sex, parents' socioeconomic status, mother's age, single parent, # coresiding household adults, # coresiding siblings, length of residence	Hierarchical linear models	Neighbourhood effects are relatively modest, operate indirectly via their effect on parenting and peer groups, and are transmitted through neighbourhood social organization, rather than neighbourhood structure
Anderson 2002	United States Self-reported Quest Schools: n=35 Adolescents: 4671 aged 13 to 15 Cross-sectional	School	Self-reported delinquency: Status, property and crime offenses	**School Level** % single parent families **Individual Level** Mother's education, sex minority status	Hierarchical linear model	The school-level single-parent family is significantly related to person offenses and marginally related to status and property offenses
Regoeczi, 2003	Canada Self-reported Quest 1990 Census 1986 EA 1206 residents cross-sectional	Enumeration Areas (EA)	Aggression and withdrawal	**Neighbourhood Level** neighbourhood density, % non-detached residences, persons per residence **Individual Level** Household density, gender, marital status, ethnicity,	Hierarchical multinomial modelling	Effects of neighbourhood's density on aggressive and withdrawn behaviour are nonlinear in nature and that the impact of household density is conditional on neighbourhood density.

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
				household income		
Beyers, et al. 2003	United States Self-reported Quest Caretakers' Quest Teachers reports Youth11–13 yrs old n=585 Transversal	Neighbourhoods	Externalizing behaviour	**Neighbourhood Level** Neighbourhood structural disadvantage, residential instability, and concentrated affluence **Individual Level** parental practices age, Ethnicity single-parent status Socioeconomic status	Hierarchical linear modelling	No effects of neighbourhood structure in externalizing behaviour; neighbourhood structure only indirectly predicted initial levels of externalizing behaviour residential instability was associated with worse behaviour problems among adolescents whose parents reported low Monitoring
Cleveland 2003	United States Self-reported Quest 16 yrs-old siblings n=2,342	Neighbourhood	Aggression: physical fight, carrying a weapon, using a weapon/knife	**Neighbourhood level** Neighbourhood disadvantage Urbanicity **Individual level** Race, age, gender	ANOVA	Disadvantaged neighbourhoods Significantly increases aggression There are also significant Cross-level interactions
Tolan, et al. 2003	United States Self-reported Quest Caretakers' Quest Adolescent boys n=294 Longitudinal	Neighbourhoods	Involvement in violence (assault, aggravated assault, sexual assault, attempted murder, and mayhem)	**Neighbourhood Level** Ethnic heterogeneity, concentration of poverty, economic resources, violent crime level, Neighbourliness, Extent of N'hood Problems **Individual Level** parenting practices, peer violence and gang membership	Structural equation modelling	Direct effect of Community Structural Characteristics on Individual violence was significant and negative. N'hood social processes, Parenting practices, gang membership, and peer violence. significantly strengthened the relation

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
Obeidallah, et al. 2004	United States Self-reported Quest Caretakers' Quest 80 Neighbourhoods Adolescents girls 12-15 yrs old n= 501 Longitudinal	Neighbourhood	Violent behaviour (thrown an object, attack with weapon, been in a gang fight, carrying a gun)	**Neighbourhood Level** Concentrated disadvantage, immigration concentration, residential mobility **Individual Level** Menarque, depressive symptoms, single parents, annual household income, educational attainment, occupational prestige, girl's age previous violent	Hierarchical nonlinear models	Early matures engaged in violent behaviour only if they life in neighbourhoods characterized by high concentrated disadvantage
Kling et al. 2005	United States Police records Caretakers' Quest Self-reported Quest 3 treatment groups 4248 household Youth 15-25 yrs old n=1807 Randomized mobility experiment	Treatment groups	Violent arrest, property arrests, drug arrests, other arrests	**Neighbourhood Level** Neighbourhood mobility to low-poverty areas **Individual Level** Sex, age, race, behaviour problems, learning problems, parent's SES, public housing parent's education, mother's age at youth' birth	Linear regression model	Moving to lower poverty neighbourhoods leads to fewer violent and property crime arrests for females, and fewer violent but more property crime arrests for males

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
Romano et al. 2005	Canada Self-reported Quest 1996 Census 96 tracts families: n=1982 children 2-11 yrs old n=2745 cross-sectional	Census Tracts	Physical aggression and prosocial behaviour	**Neighbourhood Level** neighbourhood poverty; neighbourhood problems; neighbourhood collective efficacy; **Individual Level** SES; mother's depression; family functioning; social support; parenting; sex; age	Hierarchical linear model	Both childhood behaviours are not necessarily related to living in poor neighbourhoods. Individual and family characteristics have more impact than neighbourhoods
Simons et al. 2005	United States Self-reported Quest 36 community-clusters 10-12 yrs old wave-1 and 12-14 yrs-old wave-2 n=633 Longitudinal	Neighbourhoods	Delinquency: Shoplifting, physical assault, lying, setting fires, cruelty to animals, vandalism, burglary and robbery	**Neighbourhood level** Collective efficacy, social cohesion, concentrated disadvantage and residential instability	Structural Equation Modelling	Collective efficacy significantly increased the probability of Delinquency. There are significant cross-level Interactions
Coster et al. 2006	United States Self-reported Quest Caretakers' Quest 132 schools Adolescents 12-21 yrs old n=11207 Longitudinal	Schools	Serious violent delinquency (serious fight, used weapon in fight, threatened weapon to get something, hurt/shot/ stabbed someone)	**Neighbourhood Level** Urban, community disadvantage, network closure, parent's participation organizations, collective supervision, family cohesiveness, deviant peer association, accessibility of guns, witness serious violence, expectation of lethal victimization, past violent victimization **Individual Level** Sex, race, Latino, age, female-headship, parent education, parent receiving	Logistic regression model	Living in disadvantages communities translates into a higher likelihood of youth violence

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
				public assistance, young involvement in prior violence		
Haynie & et al. 2006 Hoffmann, 2006	United States Self-reported Quest 2,449 census tract Adolescents 12-21 yrs old n=12747 Longitudinal United States Caretakers' Quest Self-reported Quest 1612 communities Adolescents n=10286	Census tracks Community (Zipcode)	Violence: physical fight, carrying a weapon, using a weapon/knife Problem behaviours (fighting, getting suspended or expelled from school, being arrested)	**Neighbourhood Level** Socioeconomic disadvantage, residential instability, immigrant concentration and population sized **Individual level** Family background demographic characteristics, family resources and parenting practices **Neighbourhood Level** % female-headed household, segregation index, % jobless males, % below poverty level **Individual Level**	Hierarchical linear modelling Multilevel regression model	Neighbourhood socio-economic Disadvantage is positively related to adolescent violence Over and beyond individual-level Characteristics Adolescents living in communities with a high proportion of impoverished residents, female household or jobless males reported more problem behaviours independent of family structure

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
				Family structure, sex, race, family income, parental supervision, family moves, school participation, peer expectations, stressful life events, parental attachment, conventional definitions		
Ingoldsby et al. 2006	United States Caretakers' Quest Self-reported Quest 1990 Census Children 5-11 yrs old n=218 Longitudinal	Census tracts	Child/Youth antisocial behaviour (fights, physically attacks people, stealing, lying or cheating/ delinquency, substance abuse, other offenses)	**Neighbourhood Level** Neighbourhood disadvantage, neighbourhood problems **Individual Level** Parent-child conflict, deviant neighbourhood peers, family income, maternal education, child ethnicity	Logistic and multinomial logistic regressions	In early childhood, neighbourhood disadvantage and family conflict place children at risk for early-starting trajectories of antisocial Behaviour
Chung and Steinberg 2006	United States Self-reported Quest 72 neighborhoods 14–18-year-old boys n= 488 Longitudinal	Neighbourhoods	Offending behaviour (car-motorcycle theft, prostitution, aggravated assault, arson, murder, armed robbery	**Neighbourhood Level** Concentrated poverty, residential instability, ethnic diversity, n'hood disorder and social cohesion **Individual Level** Parental education Parenting behaviour Peer deviance	Structural equation modelling	Weak n'hood social organization is indirectly related to delinquency through its associations with parenting behaviour and peer deviance

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
Frank, Cerdá and Rendón 2007	United States Self-reported Quest 65 Census tracts 12-17 adolescents N=890 Cross-sectional	Neighbourhood	Delinquent behaviour: sexual activity, gang membership, ran away from home and gun ownership	**Neighbourhood level** Neighbourhood poverty, concentration of Latinos, African Americans and immigrants social cohesion, social organization informal social control and collective efficacy **Individual level** # children household, sex/age/race, education/ occupation of parent, language Spoken, welfare receipt, marital status, Residential history, family income, home Ownership, family structure, church attendance, parent-child relationship, family problems, documented status and time arrival in the US	Three-level Rasch model With random effects	Residences in areas with higher levels than the city-average of Latinos significantly affected individual level measures of adolescent delinquent behaviour significant cross-level interaction effects
Kohen et al. 2008	Canada 1996 Census Caretakers' Quest 2769 EA Children 4-5 years old n= 3528 cross-sectional	Enumeration Areas	Verbal ability and behaviour problems (hyperactivity, prosocial behaviour, emotional disorder, indirect aggression, property offense)	**Neighbourhood Level** Neighbourhood structural disadvantage, neighbourhood cohesion, **Individual Level** Family disadvantage, maternal depression, family functioning, literacy in the home, consistent parenting, punitive	Linear regression model	There was not significant overall or total effect of neighbourhood structural disadvantage on children outcomes. It had indirect associations with children's outcomes through both neighbourhood and family level processes.

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
				parenting		
Mrug & Windle 2008	United States Self-reported Quest Parents and teachers' Quest Preadolescents n=704 cross-sectional	Neighbourhood	Externalizing behaviour: Delinquency Deviant behaviour, Disruptive behaviour	**Neighbourhood Level** N'hood concentrated poverty, N'hood Location socioeconomic status, residential stability, ethnic heterogeneity, n'hood social and physical disorder **Individual Level** Gender, ethnicity, parenting, family SES peer deviant behaviour	Hierarchical multilevel analysis	N'hood disadvantage, ethnic heterogeneity, and low residential stability affect children's behaviour indirectly through their impact on neighbourhood social processes, which in turn influence parenting and deviant peer affiliations.
Molnar et al. 2008	United States Self-reported Quest 9–15 years old youths N=2,226 80 neighbourhoods Longitudinal	Neighbourhoods	Juvenile aggression and delinquency	**Neighbourhood level** Concentrated poverty, organizations and services **Individual level** Family socioeconomic position was a composite of parental income, educational level, and occupational code	Generalized Estimating Equations with a logit link function	Organizations and services negatively related to aggression. This neighbourhood condition also moderates the effect of family, peer, and mentor resources
Karriker-Jaffe et al. 2009	United States Self-reported Quest 128 neighbourhoods 13.1 years old adolescents n = 5118 Longitudinal	Neighbourhoods	Fighting, hit or slapped, threatening with/without a weapon	**Neighbourhood level** Socioeconomic disadvantage, social organization, social bonding, social control **Individual level** Race/ethnicity, parent education, family structure, number of moving nhood,	Multilevel growth model	Neighbourhood disadvantage was associated with female . aggression independent of the Level of social disorganization

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
				type of address geocoded and precision		
Jennings et al. 2010	United States Self-reported Quest Children aged 11 to 14 N=5812 Schools N=61 Longitudinal	Neighbourhood	Physical aggression: involvement in hit or beat up, physical fight, threats	Neighbourhood problems	Hierarchical linear modelling	Neighbourhood problems had significant effects on adolescent physical aggression Above and beyond individual-level variables
Zimmerman 2010	United States Self-reported Quest 78 neighbourhood 12 and 15 yrs-old adolescents n=1191 Longitudinal	Neighbourhood	Violent and property crime: hitting someone, using a weapon; throwing objects, carrying a weapon; setting fire to properties, stealing, participating in a gang , fight, breaking and entering, stealing from a store/car and buying/selling stolen goods	**Neighbourhood level** concentrated disadvantage, immigrant concentration, residential instability, collective efficacy, criminogenic behaviour moral/legal cynicism **Individual level** Age, sex, ethnicity, family SES, family Structure and # yrs current residence	Multilevel logistic Regression models	Neighbourhood socioeconomic status, collective efficacy, and lower levels of criminogenic behaviour settings and moral/legal cynicism significantly moderate the effect of impulsivity on violent and property offending
Zimmerman and Messner 2010	United States Self-reported Quest 78 neighbourhood 12 and 15 yrs-old adolescents n=1502 Longitudinal	Neighbourhood	Violent and crime: (defined as above study)	**Neighbourhood level** neighbourhood concentrated disadvantage, immigrant concentration, and residential instability **Individual level** Gender, age, race/ethnicity, immigrant Generational status, internalizing and Externalizing behaviour problems, self-control and IQ	Multilevel logistic Regression models	Net of individual control variables, neighbourhood concentrated disadvantage was associated with higher adolescent violent crime

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
Europe						
Dahlback 1996	Sewden Authorities' registers Police' registers 49 Sub-areas Males 15-25 yrs old n=7719 Cross-sectional Longitudinal	City	Criminality (suspected perpetror of violent crimes, theft, fraud, vandalism, traffic violations, drugs violations and other crimes)	**Neighbourhood Level** Level of criminality **Individual Level** Socio-economic status, family conditions	Variance analyses	Area of residence does not have any statistical relationship with criminality in any period
Kalff et al. 2001	Netherlands Caretakers' Quest 36 neighbourhoods Children 5-7 yrs old n=734 cross-sectional	Neighbourhood	Child behaviour problems: (behaviour and emotional problems)	**Neighbourhood Level** Neighbourhood socioeconomical deprivation **Individual Level** education and occupation level of the parents, parental marital status, country of birth of the parents, sex, age	Multilevel analyses	Neighbourhood socioeconomic level have an independent effect on child behaviour problems, over and above the effect of individual level socioeconomic status
Schneiders et al. 2003	Netherlands Self-reported Quest Caretakers' Quest 74 neighbourhoods Children 11-12 yrs old n=734 Longitudinal	Neighbourhood	Behavioural problems: internalising (withdrawn, somatic complains and anxious/depression) and externalising (delinquent and aggressive)	**Neighbourhood Level** Neighbourhood socioeconomical disadvantage **Individual Level** Parental education and occupation, child's gender and age	Multilevel analyses	Neighbourhood socioeconomic disadvantage was associated with greater behavioural problems in children, irrespective of family socioeconomic status

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
Oberwittler 2004	Germany Self-reported Quest Police registers 61 Neighbourhoods 2530 residents adolescents 13-16 yrs old n=6437 cross-sectional	Census Tracts	Serious offending (violence and serious property offenses)	**Neighbourhood Level** % welfare recipients<18, Intergenerational closure, mean violence tolerance **Individual Level** age, sex, immigrant background, incomplete family, SES, welfare recipient, school bonding, violence tolerance	Multilevel analyses	Contextual effects on adolescents' behaviour are very small compared with individual level influences
Williamson et al. 2005	England Police records 61 Neighbourhoods Offenders n=12310 Longitudinal	Neighbourhoods	Single/repeat offender	**Neighbourhood Level** Urban, successful neighbours, happiness, comfort, closeness, welfare, dependency **Individual Level** Gender, ethnicity, offense classification, outcome, context, age	Cumulative incidence	There are considerable variations in the level of youth offending between different neighbourhood types
Mc Vie & Norris 2006	Edinburgh Self-reported Quest Police recorded crime data 91 neighbourhoods 16 yrs-old adolescents n=4328 Longitudinal	Residential neighbourhood	Criminal offending	**Neighbourhood level** Instability, economic deprivation, street Crime, community satisfaction, community Safety, collective efficacy, incivilities, cannabis acceptance **Individual level** Gender, parents occupation (SES), Impulsivity and parental separation	Multilevel modelling	Concentration of deprivation had an independent effect on the probability of offending behaviour over and above the effect of individual-level Measures

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
Mc Vie & Norris 2006	Edinburgh Self-reported Quest Police recorded crime data 91 neighbourhoods 16 yrs-old adolescents n=4328 Longitudinal	Residential neighbourhood	Property offending	**Neighbourhood level** Economic deprivation, population instability , collective efficacy, incivilities police recorded property crime rates, **Individual level** Gender, impulsiveness, socioeconomic status and parental	Multilevel modelling	Neighbourhood informal social control significantly predicts higher levels property offending Behaviour
Weijters et al. 2007	Germany Self-reported Quest 11 cities, 185 nhoods 12-17 yr-old adolesc n= 17018	Cities and Neighbourhoods	Delinquency (vandalism, graffiti, burglary, carrying a weapon, threatening)	**Neighbourhood Level** No examined **Individual Level** Age, ethnicity, gender, educational level, home situation	Multilevel analyses	4.6% of the variance of youth Delinquency is at the neighbour-hood level, while only 0.3% At the neighbourhood level
Bernburg & Thorlindsson 2007	Iceland Self-reported Quest 68 school communities Adolescents 15-16 yrs old n=6458 cross-sectional	Public schools	Delinquency (steal, robbery, burglary, damage things, another criminal offense)	**Community Level** Community social instability, SES, urban location, proportion female **Individual Level** Embeddedness in social ties, normlessness, unsupervised peer activity, residential mobility, family disruption, parents educational attainment and occupational status, gender	Hierarchical linear model	There is a contextual effect of the community social instability on delinquency

Africa

Author(s)	Country & Data source & sample	Neighbourhood units of analysis	Dependent variables	Independent variables	Type of model	Main findings
Paschall & Hubbard 1998	Africa Self-reported Quest Caretakers' Quest Male adolescents 14-19 yrs old n=188 cross-sectional	Adolescents	Violent behaviour (pushing, kicking, or hitting; hurting someone in a fight; carrying a gun/knife using gun/knife to injure)	**Neighbourhood Level** Neighbourhood poverty family stress and conflict **Individual Level** Mothers' depression, mothers' violence behaviour, sons' exposure to violence in home, self-esteem, self-worth, sense of hope or optimism for the future, propensity for violent behaviour, delinqu friends	Linear regression model	Neighbourhood poverty was unrelated to the adolescents' propensity for violent behaviour.

Appendix 2.MLwin macros for Rasch modelling

Macro 1. Setting up the data from short to long

```
Note Rasch 1 builds the data structure for a two-level model
Note setup the data structure for a two level Rasch model
Note for M items and two level model
Note estimates MQL first order and then MCMC for 500 burnin and
5000 simulations
Note on entry, b501 is number of items
NOte on entry, b02 is the number of people including those with
missing values
calc b501=5
calc b502=1000
Note on entry, the first b501 columns contains the items
Note ensure that The First column is called Resp1 and the last one
RespFin
Name c1201 'Resp' c1202 'Persons' c1203 'Items' c1204 'Const'
Join 'Resp1'-'RespFin' 'Resp'
Note b502 is the number of people
code b501 b502 1 'Items'
code b502 1 b501 'Persons'
Aver 'Persons' b503
echo 1
print b503 b501 b502
echo 0
Note b3 is the total length of the responses, persons and items
Code 1 1 b503 'Const'
Note need to sort People then items and carry responses
SORT 2 'Persons'  'Items' carry  'Resp' out to 'Persons'  'Items'
'Resp'
Note End macro
```

Macro 2. Specifying a two-level model as Kamata and Raudenbush

```
Note Rasch 2 specifying a two-level model
Note clear the model before specifying anything
Clear
Note show the equation window
wset 15 1
Note declaring response variable
Resp 'Resp'
Note choose binomial distribution
rdist 1 0
Note logit function
lfun 0
Note linearisation to MQL first order
linea 0 1
Note set denominator
```

```
doffs 1 'Const'
Note Defining two level structure
Iden 2 'Persons'
Iden 1 'Items'
Note adding the constant into the model and removing it from the
fixed part
Addt 'Const'
Fpar 0 'Const'
Note including the constant in the level 2 (Persons) random part
of the model
Setv 2 'Const'
Note including Items variable, first make Items categorical
Ntoc 'Items'
Note create all dummies with no reference category
Addt 'Items' -1
Note show parameter estimates for the fixed and random part
EXPAND 2
ESTM 2
Note End macro
```

Macro 3. Estimating the model, first in RIGLS and then using MCMC

```
Note Rasch 3 estimation of the two-level model
Note show the equation window during estimation
wset 15 1
METHD 0
Note 50 iterations and do not pause between iterations
maxi 50
batc 1
star 1
Note Do MCMC burnin for 1000 using defaults
MCMC 0 1000 1 5.8 50 10 c1479 c1478  2 2 2 1 1 2
erase c1090 c1091 c1479 c1478
Note Do MCMC calibration for 50000 simulations
MCMC 1 50000 1 c1090  c1091 c1003 c1004 1 2
PUPN c1003 c1004
Aver c1091 b99 b100
Note End macro
```

Macro 4. Transforming item parameters into IRT results

```
Note Rasch 4 IRT formulation of item difficulty
Aver c1098 b1 b2
Calc c1200 = (-1* c1098) + (b2)
Echo 1
Say centered difficulty estimates in IRT formulation
Print c1200
Echo 0
Note End macro
```

Macro 5. Plotting a variety of graphical displays for model interpretation and for the evaluation of model fit.

```
Note Rasch 5 Postprocessing of Rasch Model
Note on exit the following graphs will be produced in the display
graphs
Note and a table with the chi-square analysis of item goodness of
fit
Note D1     ICC in logit and probabilities
Note D2     Item person map
Note D3     IIF, TIF, SEM
Note D4     Pathway for items using t infit values
Note  D5    Simple graph of the Difficulty and their CI'vs Items

Name c1225 'LgitFix' c1226 'LatTraitS'
Name c1227 'DiffS' c1228 'ID' c1229 'LatTrL'
Name  c1230  'IRFLogit'  c1231  'IRFprob'  c1232  'Zeroes'  c1233
'ItemNo'
Name c1234 'IIF' c1235 'TIF' c1236 'SEM'
Name c1237 'RawResid'
Name c1238 'Varij' c1239 'Zni' c1240 'ZniSq'
Name  c1243  'InfitPers'  c1244  'InfitItem'  c1245  'RawResSq'  c1246
'RawVar'
Name c1251 'SErrItem' c1252 'SErrLTrait'
Name  c1254  'Lowercut'  c1255  'Highcut'  c1256  'LowercutIt'  c1257
'HighcutIt'
Name c1260 'InfitPerT' c1261 'InfitItemT'
Name c1262 'LowercutT' c1263 'HighcutT' c1264 'LowercutItT' c1265
'HighcutItT'
Note get Difficulty items of length M from stored column (Beta_i)
Calc 'DiffS' = c1098
Note Estimate the latent trait for each person; ie short (Uo_j)
rfun
Rout 'LatTraitS' 'SErrLTrait'
Rlev 2
Rcov 1
RTYPE 1
mcre
calc 'SErrLTrait'= 'SErrLTrait'**0.5
Note 95% Confidence intervals as offsets
calc 'SErrLTrait'= 'SErrLTrait'*1.96
Note replicate this to each person and each item
Note first create person short
Gene b502 'ID'
Merge 'ID' 'LatTraitS' 'Persons' 'LatTrL'
Note get the difficulty estimate for every person and every item
(Beta_ij)
Pred 'LgitFix'
Note  the  Item  response  function  on  the  Logit  scale  (IRF_ij  =
Beta_ij + Uo_j
Calc 'IRFLogit' = 'LgitFix' + 'LatTrL'
Note the Item response function on the Probability scale
Calc 'IRFprob' = ALOGIT('IRFLogit')
Note create some index terms for the Item-Person map
Put b501 0  'Zeroes'
Gene b501 'ItemNo'
```

```
Note turning difficulty into IRT specification not centred
Note Easy items now have the lowest values
Calc 'DiffS' = -1 *'DiffS'
Note get the LRT version of the logit difficulty estimates
Note plot the IRF on the Logit Scale
GCLEAR
GIND 1 1
GYCO 'IRFLogit'
GXCO 'LatTrL'
GGRO 'Items'
GTYP 1
GCLR 16
GLAB 2
GTEXT 3
Gtab 1 1
GTIT 4 0 0 'IRF on Logit Scale'
GTIT 2 0 0 'Latent Trait'
GTIT 3 0 0 'Logit'
GIND 1 2

Note plot the IRF on the Probability Scale
GYCO 'IRFprob'
GXCO 'LatTrL'
GGRO 'Items'
GTYP 1
GCLR 16
GLAB 2
GTEXT 3
GCOO 0 1
GTIT 4 0 1 'IRF on Probability Scale'
GTIT 2 0 1 'Latent Trait'
GTIT 3 0 1 'Probability'
GSCA 0 1 0 0 1 4

Note Histogram the Latent trait values for each person
GIND 2 1
GLAB 0
gtab 1 1
GTYP 5
GYCO 'LatTraitS'

Note overlay the difficulty scores to get the person item map
Note these are uncentered Logits * -1
GIND 2 2
GLAB 0
GLAB 2
GTEXT 3
GYCO 'Zeroes'
GXCO 'DiffS'
GGRO 'ItemNo'
GMST 13
GCLR 16
gtab 1 1
GTIT 4 0 0 'Person Item Map'
GTIT 2 0 0 'Latent Trait'
GTIT 3 0 0 'Frequency of persons'

Note Calculate IIF as probability of Yes * Probability of No
calc 'IIF'='IRFprob'*(1-'IRFprob')
GIND 3 1
GLAB 2
```

```
gtab 1 1
GYCO 'IIF'
GXCO 'LatTrL'
GGRO 'Items'
GTYP 1
GCLR 16
GLAB 2
GTEXT 3
gtab 1 1
GTIT 4 0 0 'Item Information Function'
GTIT 2 0 0 'Latent Trait'
GTIT 3 0 0 'Information'

Note Calculate the TIF for each person by averaging across each
person
Note and multiplying by number of items

TABStore 'TIF'  'IIF'  'Persons'
calc 'TIF'= 'TIF'* B501
GIND 3 2
GLAB 0
GYCO 'TIF'
GXCO 'LatTraitS'
GTYP 1
GCLR 12
GLTH 3
GLAB 1
GTEXT 3
GCOO 0 1
gtab 1 2
GLAB 'Test IF'
GTIT 4 0 1 'Test Information Function'
GTIT 2 0 1 'Latent Trait'
GTIT 3 0 1 'Information'

Note Calculate the SEM for each person by square root of the
reciprocal TIF
calc 'SEM' = (1/'TIF')**0.5
GIND 3 3
GLAB 0
GYCO 'SEM'
GXCO 'LatTraitS'
GTYP 1
GCLR 12
GLTH 2
GCOO 0 2
gtab 1 5
GTIT 4 0 2 'Standard Error Measurement'
GTIT 2 0 2 'Latent Trait'
GTIT 3 0 2 'SEM'

Note do preparatory work for pathway graphs
Note first calculate the squared raw residual for all items and
all people
Note RawResid =observed-expected
Calc 'RawResid' = 'Resp' - 'IRFprob'
Note Calculate the variance, sometimes known as Information
Calc 'Varij' = 'IRFprob' * (1-'IRFprob')
Note standardizing the RawResiduals, standardized residual or
ZScore
Calc 'Zni' = 'RawResid' / ('varij'**0.5)
```

```
calc 'ZniSq' = 'Zni'**2
Calc 'RawResSq' ='RawResid'**2
Note outfit is unweighted total fit
Note Outfit for item = znisq averaged over item
Note Outfit for person = znisq averaged over person
Note eq 4.3 of Conquest
Note Infit statitics
Note SUM(ZniSq * Varij) for each item divided by the sum of Varij
Note calculating numerator
Name c1266 'NumSS' c1267 'TopSS' c1268 'DenomSS' c1269 'PersID'
Calc 'NumSS'='ZniSq' * 'Varij'
TABStore 'TopSS' 'NumSS' 'Items'
Calc 'TopSS' = 'TopSS' * b502
TABStore 'DenomSS' 'Varij' 'Items'
Calc 'DenomSS' = 'DenomSS' * b502
Calc 'InfitItem'='TopSS' /'DenomSS'
Say sum squares and infit ratio for items
ECHO 1
Print 'ItemNo' 'TopSS' 'DenomSS' 'InfitItem'
Echo 0
Note Outfit for Person
TABStore 'TopSS' 'NumSS' 'Persons'
Calc 'TopSS' = 'TopSS' * b501
TABStore 'DenomSS' 'Varij' 'Persons'
Calc 'DenomSS' = 'DenomSS' * b501
Calc 'InfitPers' ='TopSS' /'DenomSS'
GENErate 1 b502 1 'PersID'
Note convert C1099 to a matrix and store in group of columns G4
calc g4=sym(c1099)
   Note: compute the square root of the diagonal entries of the
   variance-covariance matrix
note: these values are the standard errors
calc 'SErrItem'=sqrt(diag(g4))
Note 95% confidence intervals for each item
calc 'SErrItem'= 'SErrItem' * 1.96
Name c1270 'Obs' c1271 'Exp' c1272 'Chisq' c1273 'P-value' c1274
'Df'
Note calculate count of number of successes by item
TABStore 'Obs' 'Resp' 'Items'
Note calculate count of number of predicted successes by item
TABStore 'Exp' 'IRFprob' 'Items'
Note turn into counts
calc 'Obs' = 'Obs' * b502
calc 'Exp' = 'Exp' * b502
Note calculate chisq value
calc 'Chisq' = (('Obs'-'Exp')**2)/ 'Exp'
Note set degrees of freedom of 1 for each test
Put b501 1  'Df'
Note calc tail probability
CPRObability 'Chisq'  'Df'  'P-value'
say 'Item analysis: low P-value values suggest lack of fit' \1
echo 1
print 'ItemNo' 'Obs' 'Exp' 'Chisq' 'P-value'
Echo 0
Note Cut-offs based on Bond & Fox for Items and Linacre for
Persons
PUT B502 0.5 'LowercutT'
PUT B502 2.0 'HighcutT'
PUT B501 0.6 'LowercutItT'
PUT B501 1.4 'HighcutItT'
Note Pathway plot for infit values
```

```
GIND 4 1
gtab 1 1
GYCO 'LatTraitS'
GXCO 'InfitPers'
GTIT 4 0 0 'Pathway for persons using MSQ Infit values'
GTIT 2 0 0 'Fit (MSQ)'
GTIT 3 0 0 'Latent trait'
GIND 4 2
GLAB 2
GYCO 'DiffS'
GXCO 'InfitItem'
GTIT 4 0 1 'Pathway for items using MSQ InFit values'
GTIT 2 0 1 'Fit (MSQ)'
GTIT 3 0 1 'Difficulty/Severity'
GCOO 0 1
GGRO 'ItemNo'
GLAB 0
GLAB 2
GTEXT 3
GIND 4 3
GLAB 0
GYCO 'LatTraitS'
GXCO 'LowercutT'
GTYP 1
GCLR 12
GLTH 2
GCOO 0 0
GIND 4 4
GYCO 'LatTraitS'
GXCO 'HighcutT'
GTYP 1
GCLR 12
GLTH 2
GIND 4 5
GYCO 'DiffS'
GXCO 'LowercutItT'
GTYP 1
GCLR 12
GLTH 2
GCOO 0 1
GIND 4 6
GYCO 'DiffS'
GXCO 'HighcutItT'
GTYP 1
GCLR 12
GLTH 2
GCOO 0 1
Note  D5    Simple graph of the Difficulty and their CI'vs Items
GIND 5 1
GYCO c1227
GXCO c1233
GSSZ 30
GYER 1 c1251
GYER 2 c1251
gtab 1 1
GTIT 4 0 0 'Item difficulty/severity: Low values are easy items'
GTIT 2 0 0 'Item Number'
GTIT 3 0 0 'Difficulty Logit'
Note End macro
```

Appendix 3. Profile for the individual latent classes and probability of response of each indicator variable

Latent construct	Class 1	Class 2	Class 3	Class 4
Harsh discipline	Moderate	High	Low	
Class memberships	0.26	0.05	0.69	
Your mother or the person who replaced her, hits you or used to hit you with her hand?	0.73	0.68	0.07	
Your mother or the person who replaced her, hits you or used to hit you whit a belt, shoe or another object?	0.64	0.71	0.01	
Your mother or the person who replaced her, hits you or used to hit you too hard that causes (caused) you bruises, injuries, bleeding or the necessity to see the doctor?	0.13	0.40	0.00	
Your father or the person who replaced him, shout you, insult you or threat with hit you?	0.17	0.82	0.03	
Your father or the person who replaced him, hits you or used to hit you with his hand?	0.28	0.94	0.02	
Your father or the person who replaced him, hits you or used to hit you whit a belt, shoe or another object?	0.22	1.00	0.01	
Your father or the person who replaced him, hits you or used to hit you too hard that causes (caused) you bruises, injuries, bleeding or the necessity to see the doctor?	0.01	0.68	0.00	
Deviant Peers	High	Low	Moderate	
Class memberships	0.10	0.27	0.63	
How many of your friends smoke illegal drugs?	0.64	0.04	0.18	
How many of your friends sell illegal drugs?	0.27	0.01	0.01	
How many of your friends sell contrabands products?	0.19	0.02	0.02	
How many of your friends lie very often?	0.88	0.37	0.87	
How many of your friends cheat in the school evaluations?	0.96	0.41	0.89	
How many of your friends cheat in a group games or sport teams?	0.70	0.05	0.39	
How many of your friends cheat in business?	0.66	0.00	0.11	
How many of your friends steal or had stolen?	0.71	0.00	0.13	
How many of your friends fight (with hands)?	0.91	0.11	0.64	
How many of your friends have attacked with a knife, pocket knife or bottle to someone?	0.37	0.00	0.02	
How many of your friends have attacked with a weapon to someone?	0.13	0.00	0.00	
How many of your friends belong to a gang?	0.32	0.00	0.02	
How many of your friends belong to the FARC, AUC O ELN group?	0.10	0.00	0.00	

Latent construct	Class 1	Class 2	Class 3	Class 4
Pro-social peers	Moderate	Low	High	
Class memberships	0.31	0.16	0.53	
How many of your friends believe that the religious principles are very important?	0.99	0.00	0.95	
How many of your friends attend religious events very often?	0.87	0.14	0.94	
How many of your friends are the best students in their courses?	0.64	0.34	0.89	
How many of your friends practice exercises very often?	0.78	0.73	0.99	
How many of your friends are sport champions or outstanding sport man?	0.30	0.39	0.90	
How many of your friends have a hobby like paint, music or literature?	0.30	0.31	0.92	
How many of your friends belong to groups that help to the neighbourhood, school or community?	0.10	0.24	0.79	
Parental Stress (stressful life events last 12 months)	No	Yes		
Class memberships	0.86	0.14		
Have someone in your family ever suffered a seriously ill or accident?	0.10	0.27		
Have you ever suffered a seriously ill or accident?	0.05	0.10		
Have someone in your family died for a natural cause?	0.02	0.05		
Does the head-family of your family lost his/her job? (father, mother or brother)	0.03	0.66		
Have someone in your family (who live or not with you and give money to help your family) lost his/her job?	0.02	0.63		
Have happened a very important decrease in your family income?	0.08	0.90		
Monitoring and supervision	Low Both	High Both	High Mother/Low Father	Low Mother/ High Father
Class memberships	0.34	0.39	0.19	0.08
Do you feel that your parents supervise you and know many things about you?	0.54	0.68	0.65	0.57
Your mother or the person who replaced her, knows where you are when you go out?	0.11	0.99	0.95	0.35
Your mother or the person who replaced her, knows who you are with when you go out?	0.05	0.99	0.98	0.35
Your mother or the person who replaced her, knows what are you doing when you go out?	0.02	0.99	0.84	0.06
Your father or the person who replaced him, knows where you are when you go out?	0.04	0.98	0.13	0.83
Your father or the person who replaced him, knows who you are with when you go out?	0.00	0.99	0.04	0.94

Latent construct	Class 1	Class 2	Class 3	Class 4
Your father or the person who replaced him, knows what are you doing when you go out?	0.01	0.96	0.01	0.75
Witness of violence at home (Lifetime)	**Yes**	**No**		
Class memberships	0.06	0.94		
Have seen someone telling hurting things to others?	0.29	0.03		
Have you seen someone humiliating or despising someone?	0.36	0.02		
Have you seen someone take advantage of others?	0.31	0.01		
Have you seen someone fighting or hitting with hands to someone indefensible?	0.03	0.00		
Have you seen someone hitting someone else with an object?	0.35	0.01		
Have you seen someone throwing an object to someone to hurt him/her?	0.34	0.02		
Have you seen someone stolen with a gun to?	0.19	0.01		
Have you seen someone hurting someone else with a knife or sharp gun?	0.01	0.00		
Have you seen someone that has been shot with a gun fire?	0.02	0.00		
Have you seen someone being injured?	0.00	0.00		
Have you seen someone being killed?	0.00	0.00		
Have you seen someone being raped?	0.00	0.00		
Have you seen someone touching private body areas of someone else without consent?	0.00	0.00		
Have seen someone telling hurting things to others?	0.01	0.00		
Victim of violence anywhere (lifetime)	**Minor**	**Moderate**	**Severe**	
Class memberships	**0.27**	**0.57**	**0.16**	
Have people made fun of you or made a bad practical joke to you?	0.32	0.72	0.88	
Have someone told you hurting things?	0.12	0.63	0.85	
Have someone despised you or humiliated?	0.00	0.40	0.66	
Have someone taken advantage of you?	0.00	0.10	0.35	
Have someone hit you with hands?	0.11	0.37	0.86	
Have someone hit you with an object?	0.18	0.40	0.77	
Have someone thrown an object to you to hurt you?	0.09	0.19	0.75	
Have someone stolen something from you with a gun?	0.04	0.04	0.16	
Have someone attacked you with a knife or another sharp gun?	0.01	0.02	0.21	
Have someone shot you with a gun fire?	0.01	0.00	0.04	
Have someone left you a wound or injury?	0.01	0.00	0.13	
Have you been raped?	0.00	0.00	0.05	
Have you been touched without consent by someone else?	0.00	0.02	0.15	
Have you been sexually caressed without consent?	0.01	0.07	0.23	

Appendix 4. Mplus syntax to estimate indirect effects of the structural neighbourhood conditions on aggressive behaviour

Single-step MSEM model.

```
TITLE:          MSEM model investigating hypothesis 1
DATA:    FILE IS Agg_PathAnalysis.dat;
VARIABLE:       NAMES ARE AdolesID Nhood Age FliaSES
                Gender Studying
                FamCrim Deviant Prosocia Monitor Harsh
                Witness Victim Stress Cons zPSD zNhoodCt
                zSocCoh zInstitu zPolice zParks zCult
                zHomi zDepr GMSES GMStudy GMFCrim GMWit
                GMstress GMdev GMpros GMMon GMHarsh
                GMVict Violent1 Violent2 Violent3
                Violent4 Overall1 Overall2 Overall3
                Overall4 Overall5 Overall6 Overall7
                Overall8 Overall9 Over10;


                USEVARIABLES = Age FliaSES Gender
                Studying FamCrim Deviant Prosocia
                Monitor Harsh Witness Victim Stress
                zPSD zNhoodCt zSocCoh zInstitu zDepr
                zPolice zParks zCult zHomi Violent1
                Violent2 Violent3 Violent4
                Overall1Overall2 Overall3 Overall4
                Overall5 Overall6 Overall7 Overall8
                Overall9 Over10;

    MISSING = all (-999);

                CATEGORICAL ARE Age FliaSES Gender
                Studying FamCrim Witness
                Victim Stress Harsh Monitor Deviant
                Prosocia Violent1 Violent2 Violent3
                Violent4 Overall1Overall2 Overall3
                Overall4 Overall5 Overall6 Overall7
                Overall8 Overall9 Over10;

    IDVARIABLE IS AdolesID;
```

```
    CLUSTER = Nhood;

                 WITHIN = Age FliaSES Gender Studying
                 FamCrim Witness Victim Stress;

                 BETWEEN = zPSD zNhoodCt zSocCoh zInstitu
                 zDepr zPolice zParks zCult zHomi ;

ANALYSIS:  TYPE IS TWOLEVEL;
    ESTIMATOR = WLSM;

MODEL:
    %within%
    W_OA BY Overall1-Over10;
    W_VA BY Violent1-Violent4;

    W_OA W_VA; ! Estimate level-1 variances;

                 W_OA W_VA ON Harsh Monitor Deviant
                 Prosocia Age FliaSES Gender Studying
                 FamCrim Witness Victim Stress;


    %BETWEEN%
    B_OA BY Overall1-Over10;
    Overall1-Over10@0;

    B_VA BY Violent1-Violent4;
    Violent1-Violent4@0;

                 zDepr zPSD zInstitu Harsh Monitor
                 Deviant Prosocia zSocCoh zNhoodCt B_OA
                 B_VA; ! estimate Level-2 (residual)
                 variances for x, m, and y

    B_OA ON zSocCoh(b1)
      zNhoodCt(b2)
      Harsh(b3)
      Monitor(b4)
      Deviant(b5)
                   Prosocia
                  zDepr zPSD zInstitu zPolice zParks
                  zCult zHomi ;

    B_VA ON zSocCoh(b6)
      zNhoodCt(b7)
      Harsh(b8)
      Monitor(b9)
      Deviant(b10)
                   Prosocia
```

```
                    zDepr   zPSD   zInstitu   zPolice
                    zParks zCult zHomi ;


    zSocCoh ON zDepr(a1)
       zPSD (a2)
       zInstitu(a3)
       zPolice zParks zCult zHomi ;

    zNhoodCt ON zDepr(a4)
       zPSD(a5)
       zInstitu(a6)
       zPolice zParks zCult zHomi ;

    Harsh ON zDepr(a7)
       zPSD(a8)
       zInstitu(a9)
       zPolice zParks zCult zHomi ;

    Monitor ON zDepr(a10)
       zPSD(a11)
       zInstitu(a12)
       zPolice zParks zCult zHomi ;

    Deviant ON zDepr(a13)
       zPSD(a14)
       zInstitu(a15)
       zPolice zParks zCult zHomi ;

              Prosocia ON zDepr
       zPSD
       zInstitu
       zPolice zParks zCult zHomi ;


MODEL CONSTRAINT:
             NEW(a1b1 a4b2 a7b3 a10b4 a13b5 a2b1 a5b2
             a8b3 a11b4 a14b5
    a3b1 a6b2 a9b3 a12b4 a15b5 totalO
          a1b6 a4b7 a7b8 a10b9 a13b10 a2b6 a5b7 a8b8
         a11b9 a14b10
    a3b6 a6b7 a9b8 a12b9 a15b10 totalV total);

    a1b1 = a1*b1;
    a4b2 =a4*b2 ;
    a7b3 =a7*b3 ;
    a10b4 = a10*b4;
    a13b5 =a13*b5 ;
    a2b1 = a2*b1;
    a5b2 =a5*b2 ;
    a8b3 = a8*b3;
```

```
    a11b4 =a11*b4;
    a14b5 = a14*b5;
    a3b1 =a3*b1 ;
    a6b2 = a6*b2;
    a9b3 =a9*b3 ;
    a12b4 = a12*b4;
    a15b5 = a15*b5;
    totalO=a1b1 + a4b2 + a7b3 + a10b4 + a13b5 + a2b1 +
a5b2 +a8b3 + a11b4 + a14b5 + a3b1 + a6b2 + a9b3 + a12b4
+ a15b5;

    a1b6 = a1*b6;
    a4b7 =a4*b7 ;
    a7b8 =a7*b8 ;
    a10b9 = a10*b9;
    a13b10=a13*b10;
    a2b6 = a2*b6;
    a5b7 =a5*b7 ;
    a8b8 = a8*b8;
    a11b9 =a11*b9;
    a14b10= a14*b10;
    a3b6 =a3*b6 ;
    a6b7 = a6*b7;
    a9b8 =a9*b8 ;
    a12b9 = a12*b9;
    a15b10= a15*b10;
              totalV=a1b6 + a4b7 + a7b8 + a10b9 +
              a13b10 + a2b6 + a5b7 +a8b8 + a11b9 +
              a14b10 + a3b6 + a6b7 + a9b8 + a12b9 +
              a15b10;

    total=totalO + totalV;

 OUTPUT: STAND ;
```

Multiple-step MSEM model.

```
TITLE:          MSEM aggression hypothesis 2
DATA:      FILE IS Aggression_MSEM_Sep2011.dat;
VARIABLE:       NAMES ARE AdolesID Nhood Age FliaSES
Gender Study FamCrim
                Deviant Prosocia Monitor Harsh Witness
                Victim Stress Violent1 Violent2 Violent3
                Violent4 Over1 Over2 Over3 Over4 Over5
                Over6 Over7 Over8 Over9 Over10
                SEClass_06 GMFSES GMStudy GMFCrim GMWit
```

```
                GMStres GMDev GMPros GMMonito GMHarsh
                GMVictim PSD ChildCtrl NhdCtrl SocCohes
                InfoSCtrl ColEffic Institu Depri Homi
                Police ParksRec Culture Education Health
                zPSD zChildCt zNhdCt zSocCoh zInfoSC
                zColEff zInstitu zDepr zHomi zPolice
                zParkRec zCult zEducat zHealthWA;

                USEVARIABLES = Age FliaSES Gender Study
                FamCrim Deviant Monitor Harsh Witness
                     Victim   Stress   zPSD   zColEff
                     zInstitu  zDepr  zPolice  zParkRec
                zCult zHomi Violent1 Violent2 Violent3
                Violent4 Over1 Over2 Over3 Over4 Over5
                Over6 Over7 Over8  Over9 Over10;

     MISSING = all (-9999);

                CATEGORICAL ARE Age FliaSES Gender Study
                FamCrim Witness
                Victim Stress Harsh Monitor Deviant
                Violent1 Violent2 Violent3 Violent4
                Over1 Over2 Over3 Over4 Over5 Over6
                Over7 Over8 Over9 Over10;

     IDVARIABLE IS AdolesID;

     CLUSTER = Nhood;

                WITHIN = Age FliaSES Gender Study
                FamCrim Witness Victim Stress;

                BETWEEN = zPSD zColEff zInstitu zDepr
                zPolice zParkRec zCult zHomi ;

ANALYSIS:       TYPE IS TWOLEVEL;
     ESTIMATOR = WLSM;
MODEL:
     %within%
     W_OA BY Over1-Over10;
     W_VA BY Violent1-Violent4;

     W_OA W_VA ; !Estimate level-1 variances;

     W_OA ON Harsh
       Monitor
       Deviant(e2)
       Age FliaSES Gender Study FamCrim
       Witness Victim Stress;

     W_VA ON H-arsh
```

```
  Monitor
  Deviant(e5)
  Age FliaSES Gender Study FamCrim
  Witness Victim Stress;

Deviant ON Monitor(d1)
   Harsh(d2);

%BETWEEN%

B_OA BY Over1-Over10;
Over1-Over10@0;

B_VA BY Violent1-Violent4;
Violent1-Violent4@0;

           zDepr   zPSD   zInstitu   Harsh   Monitor
           Deviant zColEff B_OA B_VA;

B_OA ON Deviant(f2)
  zColEff zDepr zPSD zInstitu zPolice
  zParkRec zCult zHomi ;

B_VA ON Deviant(f5)
  zColEff zDepr zPSD zInstitu zPolice
  zParkRec zCult zHomi ;

Deviant ON Monitor(c1)
   Harsh(c2);

Monitor ON zDepr(b1)
   zPSD(b2)
   zInstitu(b3)
                      zColEff    zPolice    zParkRec
                     zCult zHomi ;

Harsh ON zDepr(b4)
   zPSD(b5)
   zInstitu(b6)
                zColEff   zPolice   zParkRec   zCult
                zHomi

MODEL CONSTRAINT:
               NEW(b1c1f2 b1c1f5 b2c1f2 b2c1f5 b3c1f2
               b3c1f5  b4c2f2  b4c2f5  b5c2f2  b5c2f5
               b6c2f2 b6c2f5 d1e2 d1e5 d2e2 d2e5);


 b1c1f2 = b1*c1*f2;
 b1c1f5 = b1*c1*f5;
 b2c1f2 = b2*c1*f2;
```

```
    b2c1f5 = b2*c1*f5;
    b3c1f2 = b3*c1*f2;
    b3c1f5 = b3*c1*f5;
    b4c2f2 = b4*c2*f2;
    b4c2f5 = b4*c2*f5;
    b5c2f2 = b5*c2*f2;
    b5c2f5 = b5*c2*f5;
    b6c2f2 = b6*c2*f2;
    b6c2f5 = b6*c2*f5;

OUTPUT: STAND CINTERVAL TECH1;
```