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Re-Balancing Routine Activity and Social Disorganization Theories in the Explanation of Urban Violence

A New Approach to the Analysis of Spatial Crime Patterns Based on Population at Risk

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Re-Balancing Routine Activity and Social Disorganization Theories in the Explanation of Urban Violence. A New Approach to the Analysis of Spatial Crime Patterns Based on Population at Risk

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Abstract: In recent research on intra-urban distributions of violent crimes, both social disorganization and routine activity theories (as well as interactions between them) have received much attention. Routine activity variables as non-residential land use usually yield high coefficients in regression models. However, the analysis of spatial patterns of personal crimes is hampered by the fact that crime rates are usually highest in city centers, where a large number of non-residential population add to the total population at risk. As empirical data on the non-residential population is normally unavailable, crime rates for central city areas are often grossly inflated, and correlations between non-residential land use and crime may be spurious.
In this paper, a new strategy of estimating population at risk using passenger count data as a proxy variable is proposed, and consequences for the explanation of census-tract level crime distributions are discussed, using calls-for-service and census data from Cologne/Germany. The use of this new denominator for computing crime rates results in a re-balancing of the relative influence of routine activity and disorganization/deprivation variables, the former losing some of their influence.

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1. Background

Spatial theories of crime deal with the non-random distribution of criminal events across places and small areas, mostly within cities, trying to explain spatial patterns and ultimately addressing the question whether spatial units can be generators of crime (Anselin et al., 2000; Bursik Jr., 2001; Eck and Weisburd, 1995; Wikström 1998). ‘Place’ in the ‘ecology of crime’ literature denotes a single physical entity as a hotel, a parking lot, or a residential block (Sherman et al., 1989, 31); ‘small area’ is a less well-defined expression which often describes small and relatively homogenous spatial units as city blocks or face blocks.

There are two theoretical approaches most frequently used for the explanation of intra-urban crime patterns. First, the ‘classical’ approach of social disorganization theory – also called ‘systemic crime model’ – focuses on the ability of local residents to enforce effective informal control over their area which is assumed to depend on structural antecedents as concentrated disadvantage and intervening social processes as social networks, and also on previous crime experiences (Bellair, 2000; Liska and Warner, 1991; Sampson et al., 1997, 2001, Warner and Rountree, 1997). In multivariate models, there often remain also direct effects of structural conditions on crime outcomes indicating that absolute or relative deprivation may be a motivational force for people to use violence (and to do so near their home) as hypothezised by strain and subcultural theories. I use the label ‘social disorganization’ in this broader meaning of intercorrelated structural disadvantage *and* collective social processes. However, its focus on community conditions seems to be also a weakness of social disorganization theory: It tacitly assumes that violence (as well as the social conditions to control it) are bred *locally* whereas in fact it is most prevalent in areas where local residents represent only a minority of people involved in violence.

Second, recent research on intra-urban crime patterns has been heavily influenced by routine activity approach which is basically an *ecological* theory of crime. Predatory crimes, according to Cohen and Felson (1979, 589-590), “must feed upon other [legal, DO.] activities” and hence their occurrence depends on “the convergence in time and space” of suitable targets and motivated offenders in the absence of capable guardians. Particularly relevant is the central hypothesis of Cohen and Felson that all other things being equal, changes in routine activities lead to more predatory crime by enhancing the likelihood of the convergence of potential offenders and victims in time and space, and in situations of ineffective supervision. In empirical studies, land use variables and especially the presence of bars and restaurants have often been found to be an important correlate of predatory crimes (Block and Block, 1995; Peterson et al., 2000; Roncek and Maier, 1991; Wikström 1991, 229). Hence, the routine activity approach is better suited than social disorganization theory to account for the mobility of offenders and victims which is particularly relevant for hot spots of (stranger) violence. Yet, as I will argue in this paper, explaining the spatial distribution of hot spots by the convergence of offenders and victims may come close to a tautology if the theoretically challenging question is not why there is more crime in certain places but whether and why the *crime risk* is higher in these places due to patterns of land use and routine activities.

Despite their diverging foci, social disorganization theory and routine activity approach can be viewed as supplementary rather than contradictory approaches to the explanation of spatial distributions of crime. Recent attempts to paint a more holistic picture of the micro-ecology of crime integrate propositions from both theories. In an empirical study on the face-block level in a south eastern U.S. city, Smith et al. (2000) found land use variables (number of commercial places, of bars, restaurants etc.) to be much better predictors of street robberies than social disorganization variables, although the latter had an additional indirect effect via the 'street robbery potential' of surrounding areas. Peterson et al. (2000, 56) also detected a 'sizeable' effect of bars on violent crimes when they studied tract-level distributions of crime in Ohio. Both studies also found important interaction effects between disorganization and routine activity variables. The results of these multivariate analyses confirm earlier, descriptive findings of Sherman et al. (1989) that bars and other places of leisure activities rank very high among the hot spots of predatory crimes in Minneapolis. This effect seems to be largest for less serious types of violence, especially for assault and robbery, and weaker for homicides which are more strongly linked to poverty and ethnicity (Kposowa et al., 1995; Land et al., 1990; Pridemore, 2002).

The question addressed in this paper is whether the balance between social disorganization and routine activities predictors in explaining urban crime patterns has been artificially shifted towards the latter in recent research due to the fact that non-residential land use is associated with a mobile population 'at risk' which is not properly controlled for in statistical models.

2. Computing crime risk - the 'denominator problem'

Results based on the analysis of official crime data may be seriously distorted by the fundamental problem of calculating adequate area crime rates. This 'denominator problem' affects most kinds of personal violence, particularly in public places, but is irrelevant for certain other types of offences as burglaries where the number of households is the natural denominator. Usually the *resident* population serves as the denominator for violent crime rates per 100.000, although it would make much more sense to base this rate on the true 'population at risk' which is present at a place when a crime occurs. The population at risk of victimization tends to be much larger than the resident population at places of non-residential land use just because they attract many people, thereby lowering the likelihood of any individual person of being victimized. The same holds true for traffic nodes and paths where a lot of violence occurs but where also many people are passing by.

If this is true, land use variables would in part merely be proxy variables for 'population at risk', and to the extent that this is the case correlations between non-residential land use and crime would be spurious. Taking an example from a different discipline: Assume there were more car accidents on motorways than on highways, would one conclude that motorways are more dangerous than highways if they had an even higher traffic load? Apparently, the *risk* of an accident is dependent on the number of cars which may be involved in an accident (cf. Coggon et al., 1997). Much the same is true for crime risks.

This denominator problem has been discussed for at least forty years, and although some remedies have been proposed, it usually receives little attention and remains unsolved (cf. Killias, 2002, 83). One of the earliest discussions can be found in an article by Sarah Boggs (1965, 900) in 'American Sociological Review': "As a consequence of the invalid method conventionally used, spuriously high crime rates are computed for central business districts, which contain small numbers of residents but large numbers of targets […] Although many crimes do take place in such areas, valid occurrence *rates* would be low relative to the number of potential targets or environmental opportunities for crime." More recently, Sherman et al. (1989, 44) have discussed the consequences of the denominator problem for spatial crime theory: "The nonrandom distribution of crime by place may simply be due to the nonrandom distribution of people. […] If crime is concentrated in direct proportion to the concentration of people, then there may be nothing particularly criminogenic about these places." In an extensive discussion, Wikström (1991, 194) points to the danger of mixing up the explanatory role of variables (of explaining a higher risk of crime in certain areas) and its controlling role (of simply adjusting the ‘true’ risk of crime by accounting for a higher number of targets at risks) in multivariate regression models.

It is important to notice that this problem exists only with regard to official data on violence incidences and not to victimization survey data. The reason is that in surveys usually the residents of an area are asked about victimizations *near their home* thus excluding the main bulk of violent crimes which happen in city centers. In the case of the data used in this study, only 19% of the victims of police-recorded violent offences which occurred in the central business district were residents of this district (see map 2b). Thus, while victimization surveys are more complete reports of violence suffered by local residents because they include also those events which are not reported to the police, they grossly underestimate the total amount of crime taking place in busy areas within cities.

There is a consensus that data on the non-residential, fluctuating population which would be necessary to estimate the population at risk in small areas within cities does not exist. Following the propositions of routine activity approach which drew its inspiration from human ecology, predatory crimes are the outcome of the convergence of victims and offenders in space *and* time, which means that the number of people, and hence crime risks, vary not only by area, but also by time of the day or week (Wikström 1991, 194). For example, central business districts are crowded during weekdays, shopping malls on Saturday mornings, and entertainment areas on weekend nights. Ideally, data on the movements of people would also include a time dimension.

In the absence of such data, researchers have tried several ways to deal with the problem by finding a “not too bad indirect indicator” (Wikström 1991, 194). Boggs (1965, 901) decided to use the square feet of streets as a substitute for the population at risk. Gibbs and Erickson (1975) computed a city-level “community/city population ratio” which takes into account the ecological position of a city within its surroundings. If a city is surrounded by a rural hinterland, it “is likely to be the center of a much larger community” (Gibbs and Erickson, 1975, 607) than is the case if it is located next to a larger city, and hence attracts more people (and crimes) from outside. This would be cause to an effect known as ‘negative spatial autocorrelation’ in modern spatial crime analysis (Anselin et al., 2000, 226). A rationale which is exactly opposite to this, following the idea of ‘positive spatial autocorrelation’, has been adopted by Roncek and Maier (1991, 736) who computed a ‘population potential’ of a census block by cumulating the sum of residents of the surrounding blocks weighted by their distance, because "controlling for not only how many people reside on a block, but also how many are likely to use a block merely because they are close to it, is important." However, it can be doubted whether the residents of one block would evenly diffuse to its surrounding blocks unless there are places of non-residential land use where people go about their daily routine activities. If it were a residential area, only few people from the surrounding blocks would visit it. Wikström (1991, 199) used data on the number of workforce which showed very high correlations with the distribution of violence in public within Stockholm. A more pragmatic strategy is simply to regard the city center as an outlier and to omit it from analysis (Hannon and Knap 2003; McNulty, 1999, 29, Peterson et al., 2000; Warner and Pierce, 1993, 504) or to add a 'downtown' dummy variable to account for its anomaly, which then usually displays very high coefficients (Bellair, 2000[1]; Messner and Tardiff, 1986; Warner and Rountree, 1997). However, both strategies are less than optimal because a crucial proportion of urban violence remains unexplained, or is explained merely by a dummy variable. Also, the problem of non-residential population is likely to exist beyond the city center, even if to a lesser extent and depending on urban geography. Hence, even if the city center is excluded from analysis, the denominator problem may continue to produce biased results.

3. A New Strategy – Public Transport Data

In this paper, I use public transport data as a new proxy variable for non-residential population which to my knowledge has never been tried so far. Counts of passengers entering and leaving the public transport system at nearly 700 stations and bus stops are used to estimate non-residential population for all small areas within the city. The technical procedures to derive area-based estimates of the population at risk from these data are described in more detail below.

While this data source is no accurate measure of the non-residential population either and has several disadvantages, it seems nevertheless to be a 'less bad' and more direct indicator than those used so far. First of all, passenger counts are the only systematic and reliable data collections of people traveling within the city. They are a good indicator of people's micro-level movements – also those by other transport modes – because public transport

[1] Bellair's analysis differs somewhat from the others because he uses a combined measure of official and self reported victimizations.

infrastructure has been built where there is a demand for it. When leaving the public transport system at a station or bus stop, people begin walking in public spaces. However, the time period for which he/she does so which would be an important weighting variable is unknown; a passenger might hasten into a nearby office building, or stroll around the high street for two hours. Also, the available data does not differentiate between the time of the day although stations or bus stops may have different peak hours corresponding to the type of land use of the surrounding area. Another drawback is that people using other transport modes (private cars, taxis, or bicycles) are obviously not included in these data. According to German micro-census data, 45% of people living in cities of more than 100.000 inhabitants use private cars for short-distance journeys within the city.[2] In general, it may be assumed that spatial patterns of traveling by private transport are similar to those of traveling by public transport. However, the choice of transport modes may co-vary with factors related to crime. It seems reasonable to assume, for example, that private cars are more often used for journeys in peripheral parts of the city whereas journeys to the city center are more often done by public transport because parking space is sparse and expensive. That would lead to an underestimation of non-residential population in peripheral parts of the city. On the other hand, the passenger counts used for this study do not identify the direction of journeys, and entering and leaving the transport system is weighted equally. It is therefore not possible to subtract a person who travels away from a residential suburb to another place from the population at risk in his residential area, resulting in an overestimation of the population at risk in peripheral areas.

Despite many shortcomings, public transport data may be a useful indicator of the non-residential population in small areas which can help to correct the inflation of crime rates especially in central urban areas. If this is true, this would help to re-balance the explanatory weight between social disorganization and routine activity theories, shifting some of the explanatory power ‘back’ from the latter to the former, and stripping the latter of its inflated association with spatial crime patterns due to the non-random distribution of people’s movements within cities. I expect explanatory variables representing routine activity theory as commercial land use or bars and restaurants to loose some of their predictive power on crime rates, because the concentration of crimes at these hot spots would now partly or totally be controlled for by a larger population at risk. The remaining power of these predictors should then express a ‘truer’ picture of the criminogenic role of land use and routine activities. Social disorganization predictors, in turn, should become

[2] Statistisches Bundesamt, press report, 19 April 2001.

more important for the explanation of violence. These hypotheses will be tested in this paper using multivariate regression techniques.

4. Data and Methods

4. 1 Sampling Site and Units of Analysis

This study is based upon data from Cologne, Germany's fourth largest city with a population of one million. Cologne has a highly diverse economic structure ranging from old, partly declining manufacturing industries to universities and electronic media business where it ranks first among German cities. According to police statistics of violent crimes, Cologne ranks third among major cities in Germany (Bundeskriminalamt 2004). The city is divided into 366 census tracts with a mean population of about 2.800 (slightly less than an average U.S. census tract), in most cases following meaningful patterns of land use and reflecting the historical growth of neighbourhoods and former villages within the city. These census tracts are assigned to 85 larger administrative units which will not be used in regression models in order to preserve as far as possible the homogeneity of aggregate units.

However, the distribution of residents to census tracts is very skewed, with a quarter of tracts counting less than 500 residents (18 tracts have even less than 10 residents), and about 4% of tracts counting more than 10.000 residents. This variation in population sizes across units poses methodological problems typical for ecological regression with aggregate data, the most important of which is heteroskedasticity, the unequal distribution of error variances. With a population base of only ten or twenty, meaningful crime rates cannot be calculated because each single case leads to an disproportional change in the rate, compared to a unit representing 1.000 or 10.000 people (Osgood 2000, 22). As error variance is particularly inflated in the smallest units, 50 was defined as the minimum population size of census tracts thereby excluding 36 census tracts accounting for 9,1% of the area but only 0,9% of crime incidences and only 0.05% of the total population from further analyses.[3] Krivo and Peterson (1996) and Peterson et al. (2000) have set the minimum population size to 700 which may considerably reduce heteroskedasticity but, on the other hand, may also

[3] Further 7 census tracts where excluded as outliers exhibiting anomalies with respect to important socio-demographic variables. Many of these 43 census tracts are largely inhabited, industrial or disused military areas.

lead to an undesirable bias of the remaining sample; as mentioned above, this strategy lead to the complete exclusion of the central business district from analysis. In Cologne, not only error variances, but also the frequency of violent crimes seem to be dependent on population size of tracts. The rates of violent crimes of 41 census tracts counting between 50 and 300 residents more than doubles the rate of all larger tracts.[4] Most of these small tracts are areas of mixed land use containing industrial sites, and also display higher levels of social disadvantage. Thus, it seems to be important for substantial reasons to keep these areas in the sample even if statistical problems may be exacerbated.

4.2 Police Call Data

Data on violent crimes are taken from the Police log file recording all calls to the police and other criminal cases prompting immediate police action in the City of Cologne within 12 months between May 1999 and April 2000 (see table 1 for descriptive statistics). The analysis is restricted to assault and battery and robberies as the main types of direct-contact personal violence. Homicides are a very rare event even in large cities in Germany with a victimization rate of about 2 per 100.000 inhabitants compared to about 15 per 100.000 in U.S. cities, and seem to be distributed rather randomly within cities. While these ‘calls-for-service’ data share the well-known problems of all police recorded crime indicators, they nevertheless represent the most complete and unscreened recording of crimes once a victim or third person has decided to turn to the police *in a case of emergency* (for detailed discussions, see Sherman et al., 1989, 33-36; Warner and Pierce, 1992, 496). In particular, calls-for-service data are largely unaffected by filtering processes which take place before a case is officially recorded as a crime incidence. These data have been found to comprise more cases than eventually enter official crime records (Warner and Pierce, 1993, 496). On the other hand, an often overlooked limitation is that all crimes which are reported to the police only some time after the occurrence, for example at a local police station, are not part of these data but are recorded in ‘conventional’ police registers. Hence, Calls-for-service data are strong for crimes evoking an immediate reaction by the victim, while conventional police records are more complete for crimes which are reported to the police after the crime has taken place.

[4] Because this comparison is based on the grand means of both groups of census tracts, it is not affected by unequal error variances.

In the case of Cologne, conventional police data on violence is not available on census tract level and therefore cannot be used for small-area analyses. It is possible, however, to compare the volume of crime in both data sources on the larger level of 85 administrative areas.[5] Compared to 4436 cases of assault and 1020 cases of robbery in the calls-for-service data, there are 4909 cases of assault and 1620 cases of robbery in the official crime records.[6] It seems safe to assume that while many cases may be dropped after the initial stage of police contact, an even large number of cases is in fact *not* included in the calls-for-service data. This could also affect the spatial distribution of recorded crimes within the city although the bivariate correlations of both data (rates per 100.000 residents) are still high, with r=.86 for assault and r=.85 for robbery on the level of 85 larger administrative units.[7]

The available calls-for-service data unfortunately do not allow to differentiate between acquaintance and stranger violence which would be particularly useful for this analysis because stranger violence can be assumed to be most frequent in central areas and more closely tied to the activities of people away from home. However, it is possible to differentiate between violence occurring during daytime (7.00 a.m. to 6.59 p.m.) and nighttime (7.00 p.m. to 6.59 a.m.)

4.3 Public Transport Data

The denominator for crime rates is either resident population or ‘population at risk’ which is the combined sum of residents from 8 years and of public transport passengers. The number of passengers at all 685 stations (including railway stations) and bus stops in Cologne come from two counts which took place in 1993 and 1997. In general, data from the latter count were used although some data had to be taken from the earlier count.[8] In 1993, passengers who entered or left public transport were counted separately from those who changed lines. The relative share of passengers entering/leaving of all passengers measured in 1993 was used to estimate the number of passengers entering/leaving in 1997. As every passenger

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[5] Conventional police records are only available for the calender year 1999 resulting in a slight difference in time period covered.
[6] These numbers referring to the level of 85 larger administrative units are slightly higher than those on the census tract level because some areas (agriculture, forests etc.) are not covered by the latter but included in the former.
[7] After eliminating 2 resp. 3 outliers.
[8] In 1993, passengers at all stations and bus stops were counted for a period of one week. In 1997, only passengers at underground and tram stations (which account for about 70% of passengers) were counted, without differentiating between entering/leaving or changing lines. For those stops without valid data for 1997, the 1993 counts were used instead.

was counted two times for each journey, the sum is divided by two. There are a total of 730,000 passengers per day in Cologne, with the busiest stop located in the central shopping district accounting for 47,500 passengers alone. These passenger counts were allocated to census tracts adjacent to station or stop using ArcView 3.2. For each of the 685 stations and bus stops, the GIS software identified all census tracts within a distance of 300 meters which was defined as a likely maximum walking distance. Because it is reasonable to assume that census tracts with commercial, industrial or public places attract more passengers than census tracts with only residential addresses, passengers were allocated to tracts relative to their share of non-residential addresses.[9] By this method, point data of passenger counts were assigned to multiple census tracts, and census tracts received passenger counts from multiple points.

4.4 Independent variables

Independent variables are taken partly from administrative data collected by the statistical office of Cologne, and partly from a directory of commercial places (Deutsche Telekom 1998) (see table 2 for descriptive statistics, table 3 for bivariate correlations). 'Routine activity' variables come from both sources. The addresses of fashion retailers, travel agencies, and medical surgeries have been taken from this directory, geocoded and combined to a common index of 'commercial land use' after ascertaining their unidimensionality in factor analysis. It is possible to validate this indicator using an official measure of the percentage of addresses with commercial and industrial land use; the correlation is r=.59 on the census tract level and r=.85 on the higher aggregate level. The same procedure applies to the measurement of bars, restaurants and cafés. The denominator for both indicators of opportunity structure is the area (square kilometres) of census tracts. Distance from the city center is used as an indicator of 'centrality', accounting for further, unmeasured sources of spatial influences on violence.

As a demographic indicator of routine activity theory, I selected the percentage of unmarried persons and the percentage of persons aged 60 years and older. Both are negatively correlated with each other (r=-.62) and correlated with crime rates in different directions. While unmarried persons who tend to be of younger age (the bivariate

[9] If, for example, four census tracts were in a distance of 300 meters to a station, and tract A had 60, tract B 30, and the other two tracts only 10 non-residential addresses, 60% of the passengers of that station would be allocated to tract A, 30% to tract B and the rest to tract C and D.

correlation with percentage of persons aged 21 to 34 is r=.90) and to live more often in areas near the city center are assumed to represent a lifestyle which is known from victimization research to be particularly crime prone (Lauritsen, 2001; Rountree et al., 1994), census tracts with predominantly older residents will produce less targets and opportunities for violent crimes.

Population density is defined as the population at risk (including non-resident population) per square kilometre. Population density has been regarded as a source of ecological strain producing conflicts and violence (Roncek and Maier, 1991; Warner and Pierce 1993); however, empirical evidence is mixed, as, for example, Sampson and Raudenbush (1999, 629) Morenoff et al. (2001, 540) find a strong negative relationship between this variable and different kinds of crime (cf. also Smith et al. 2000, 499). This could be explained by the effect of informal guardianship which may be tighter in densely populated areas, especially if more people are present in pubic spaces. Following this reasoning, I will use this variable as an indicator of guardianship.

Social disorganization theory is represented by the structural condition which has consistently be found to be primarily responsible for low informal control, and to have also direct effects on violence: deprivation. Because recent census or other official data on income levels are unavailable in Germany, welfare dependence is used as the sole indicator of deprivation. Ethnic heterogeneity is not used throughout the following analyses for reasons of multicollinearity, and because it is closely related not only to deprivation (r=.64) but also to indicators of routine activity theory (r=.44 with percentage unmarried, r=.28 with bars and restaurants, r=-.41 with distance to central city) which hints at an ambiguous role of this variable and renders it more difficult to clearly differentiate between the two theoretical approaches. There are a number of centrally located, gentrified and 'multi-cultural' neighbourhoods in Cologne where ethnic minorities mix with a German population predominantly of students and professionals.

For the analyses presented here, weighted least square (WLS) regression is chosen as the main modeling strategy. In order to mitigate the consequences of heteroskedasticity, the square root of population at risk as taken as weighting variable (Kmenta 1986; Messner and Tardiff, 1986; Sampson and Raudenbush, 1999). By doing so, small census tracts with possibly higher error variances have less influence on the model estimation than larger census tracts.[10]

[10] This strategy has been ignored by Osgood (2000) in his methodological discussion.

5. Results

5.1 Mapping the distributions of population at risk and crime

As a first step of analysis, attention is drawn to the spatial distribution of population at risk, the new denominator for calculating crime rates. Map 1 displays the relative proportion of passengers to the resident population and clearly shows the concentration of non-resident population in the central parts of the city. In the most extreme case of one census tract located in the midst of the central business district, the non-residential population exceeds the resident population 25-fold. All downtown census tracts together have a non-resident population which exceeds the resident population 2,3-fold, whereas this ratio in all other census tracts is 0,6. If one looks only to the central business district which comprises about a quarter of all downtown census tracts, this ratio climbs to 6,5. However, there are quite a few census tracts *outside* the city center with non-residential/residential population percentages well above 100, as can be seen in map 1. Some of the more extreme cases are peripheral enterprise zones with very few residents, but many are more centrally located urban areas with mixed land use. A simple downtown dummy variable would not capture these busy areas outside the city center. The bivariate correlation of the density of non-resident population (per square kilometre) with the density of places of commercial land use and bars and restaurants (per square kilometre) is quite strong (r=.82) and would be only slightly less strong (r=.69) if passenger counts would have been allocated evenly to census tracts, without a weight variable for land use.

Maps 2a and 2b illustrate the distribution of shares of offenders and victims who are residents in the area where the offence takes place. The central business district (northern semicircular part of city center) stands out for its extremely low shares of local offenders and victims indicating that crime in this area is overwhelmingly a matter of non-residents converging in the pursuit of their routine activities.

Next, what happens to crime rates if population at risk is chosen as denominator? When using the conventional denominator – resident population –, crime rates of assault and robbery in downtown areas by far exceed those in other parts of the city (figures 1a and 1b). Daytime assault rates in downtown areas are about 3-fold higher than elsewhere; during nighttime, the ratio climbs to about 4:1. This pattern is even more pronounced for robbery rates. When using the new denominator – population at risk – this picture changes dramatically. There is no difference in rates between downtown and the rest of the city for daytime assault, and only very slight differences for nighttime assault and daytime robbery. Only nighttime robbery is still about as twice at likely in downtown areas.

The same effect becomes quite apparent when using crime mapping techniques to visualize density surfaces of crime risks (see maps 3a and 3b). Both maps are based on geocoded calls-for-service data not yet aggregated to census tracts and represent 'dual kernel density estimates' performed in CrimeStat 2.0 (for details, see Levine, 2002, 324; Oberwittler and Wiesenhütter, 2002). If resident population is used as denominator, the city center clearly is among those areas with the highest crime risk although there are a number of hot spots in more peripheral areas, too (map 3a); if the non-resident population is added, the crime risk is dramatically reduced in the city center, whereas other hot spots remain nearly unchanged because there is few non-residential population in these areas (map 3b). Most of these hot spots are located in areas of concentrated disadvantage. These descriptive results already lend some support to the notion that the role of routine activity theory in explaining area rates of violent crime is challenged if crime risks are controlled for spatial patterns of non-residential population.

5.2. Results of regression models

To examine the effects of changing the denominator in more detail, I have computed four pairs of WLS regression models for small-area distributions of day- and nighttime assault and battery (table 4) and day- and nighttime robbery (table 5), each with resident population and population at risk as denominators. In all models, routine activity variables are entered first, followed by the deprivation variable and interaction terms of deprivation with routine activity variables where they proved significant.[11] Thus, the coefficients involved in interactions are conditional on the value of the respective other variable. On the bottom of both regression tables, the explained variance (R^2) after entering routine activity variables is given first, followed by the additional R^2 due to deprivation and interaction terms, and total adjusted R^2. These R^2 values allow for a quick assessment of how important both blocks of explanatory variables are for explaining violence. Standardized beta-coefficients and t-values are reported for each explanatory variable.

[11] Following common practice, I have centred variables before building the interaction term to reduce multicollinearity.

To begin with daytime assault and battery, 21% of variance of the resident population rate is explained by routine activity variables, whereas deprivation and interactions add about 10% of explained variance. Non-residential land use as well as the percentage of older residents affect violence in the expected direction. Population density yields the largest beta-coefficient (which only appears after controlling for land use and deprivation), and its negative sign confirms its possible role in providing guardianship against violence, although the size of this effect comes as a surprise. Yet, a variance inflation factor (VIF) of 3.7 indicates that multicollinearity may pose a problem here. The interaction between the percentage of welfare recipients and bars and restaurants is significant and affects violence negatively. As the levels of deprivation rise, the impact of this kind of land use on violence becomes less and less important, or putting it differently, bars and restaurants add relatively less to the risks of violence in areas of concentrated disadvantage.

In the model using population at risk as denominator, the shares of explained variance are almost reversed: Routine activity variables explain only 11%, and deprivation explains almost 25% of variance. Bars and restaurants (and its interaction with deprivation) and the percentage of older residents cease to be significant predictors, and the percentage of welfare recipients, in turn, leaps from b=.27 to b=.55. The effect of centrality is nearly halved; a large part of unmeasured spatial influences of central areas thus disappear when adjusting for non-resident population. In all models, the percentage of unmarried persons which has the strongest bivariate correlation with daytime assault is rendered insignificant hinting at a spurious correlation.[12]

A quite similar pattern emerges when nighttime assault and battery is the dependent variable. Violence during nighttime can be assumed to show a slightly different spatial distribution, particularly with regard to the role of bars and restaurants as hot spots of violence. Areas with many bars and restaurants should show higher levels of violence during nighttime than during daytime. Unfortunately, the existing passenger count data does not allow to estimate time-specific populations at risk. The regression models show that routine activity variables are in fact more important for explaining nighttime than daytime violence which is due both to a higher positive effect of bars and restaurants and a higher negative effect of the percentage of older population, whereas the effect of deprivation is weaker during nighttime. Comparing the population at risk rate to the conventional crime rate, there again is a shift in the relative weight of explanatory variables from routine

[12] Percentage unmarried is the only variable with a VIF larger 4 (4.4), thus multicollinearity cannot be ruled out.

activity to disorganization theory although the former remains more important (21% vs. 16,5% of explained variance). It is particularly noteworthy that bars and restaurants which are insignificant for daytime assault are (if only marginally) significant for nighttime assault. This could be seen as a confirmation of the criminogenic nature of leisure-time (and alcohol-related) routine activities. However, the question remains whether this effect would be eliminated if data on non-residential population at nighttime would be available. It can be assumed that entertainment areas which show higher levels of violence during nighttime are also more crowded during nighttime.

Residual diagnostics show that the census tract with the highest share of non-resident population also is the most extreme outlier in the regression model based on resident population denominator (studentized deleted residual = 9.6, Cook's distance = .86); When using population at risk as denominator, these values are reduced to 1.1 and .01, underlining the accurate assignment of non-residential population to census tracts and the effectiveness of this new denominator.

Table 5 reports the same set of regression models for robbery which show basically the same patterns although effect sizes and levels of explained variance are lower because incidents of robbery are much less frequent than incidences of assault and battery. Without going too much into detail, routine activity variables are generally more important for the explanation of robbery than assault and battery, probably because robbery it is typically stranger violence. Yet, the coefficients of deprivation are raised from non significant to very significant both for daytime and nighttime robbery when population at risk replaces resident population as denominator. As the 'main' effect of bars and restaurants on daytime robbery become insignificant in the model based on population at risk, so does its interaction effect with deprivation. As in the case of assault and battery, however, bars and restaurants remain a marginally significant predictor of nighttime robbery. Contrary to expectations, the percentage of unmarried persons gains a significant role in explaining nighttime robbery rates based on population at risk.

Overall, the shift from resident population to population at risk as denominator has consistent and strong effects on all violent outcomes. Routine activity variables loose much of their influence on violence, and deprivation is rendered the single strongest coefficient in all models. Routine activity variables continue to play an important role in explaining nighttime violence which can be assumed to be more strongly associated with leisure time activities. It is remarkable that a high population density (including non-residential population) which is closely associated with these leisure time activities as shopping and going to bars and restaurants seems to inhibit assault and battery.

6. Discussion

This article has been stimulated by a concern about certain aspects of recent research on intra-urban patterns and hot spots of violence, i.e. the way in which land use variables are being used as indicators of routine activities in models of crime causation. While the routine activity approach has clearly been a very important theoretical innovation to the field of spatial crime analysis and attempts to integrate this approach into 'classic' theories of crime causation should continue, it seems that some of the assertions based on land use variables have in fact been tautological, thus distorting the balance between social disorganization and routine activity theories. The reason for that distortion is that non-residential land use is always associated with a non-residential population which adds to number of people potentially involved in violence. When analyzing spatial patterns of violent crimes, particularly on the micro-level of places and small areas, it is hardly possible to escape this 'denominator problem'. As long as one is interested in the absolute number of crimes and wants to know why and where crime hot spots exist, this certainly is less of a concern. Police tactics are directed towards hot spots because violence is obviously concentrated in these places, and crime reduction efforts are likely to be most efficient if focussing on them (Eck 1997). Roncek and Maier (1991, 732) use frequencies of crime instead of crime rates as dependent variable because 'rates can be misleading for policy because police must try to plan to respond to the number of incidents […] and using population-based rates do not allow for this'. In their perspective it is preferable to use any demographic or structural variable as independent variables in a model explaining the distribution of crime incidences instead of using it as denominator. Following the logic of routine activity theory, the spatial allocation of non-resident population actually can be seen as an important independent variable which tells where people converge and hence predicts where crime happens.

However, spatial theories of crime, and routine activity theory among them, should be interested in more than predicting crime incidences; they should also try to answer the important question whether and why places or areas are crime-prone. To use the language of routine activity theory, they are not only interested in the convergence in time and place, but also in the interactions of people and places, and in the absence of capable guardians.

The concept of *risk* seems to me to be at the heart of spatial crime theories. To explain the number of robberies at a certain place by the number of people who frequent this place comes close to a tautology if the real challenge is to show which structural, environmental and situational factors shape the risk of such an event at certain places. The practical interests of police and crime prevention policies not withstanding, this risk perspective can also be assumed to be most relevant for the people themselves, their perceptions of safety and their behavior.

From this perspective, finding an appropriate denominator for crime events remains an important task. Ignoring this issue does not help, because rates based on the conventional denominator (residential population) produce biased results, as has been shown in this paper, and is also apparent from previous studies. The use of passenger counts as a proxy variable for non-residential population which was tested in this paper seems to work reasonably well in adjusting area crime rates for the population at risk which, however, still remains unknown.

The results of multivariate regression models based on both denominators have serious implications for theory development. Broadly speaking, variables representing routine activity variables are stripped of their inflated explanatory power, and the role of social disorganization theory is strengthened, when crime risks are better adjusted for populations at risk. The negative association between population density and violent assaults supports previous results that the presence of capable guardians is an important factor preventing violence. Most importantly, however, structural disadvantage and its concomitants seem to have a pivotal role in shaping urban patterns of violence. It would be interesting to apply the method proposed in this article to data from other cities to see whether these conclusions can be generalized.

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Tab 1. Descriptive statistics of dependent variables (Cologne 1999/2000, N=323 census tracts)

	minimum	maximum	mean	std. dev.
assault and battery (N=4227)				
daytime incidences (N=1985)[a]	0	62	6,15	8,50
rate per 100.000 residents	0,00	3731,34	287,37	470,72
rate per 100.000 population at risk	0,00	2710,29	164,06	264,96
night-time incidences (N=2236)[b]	0	108	6,92	11,72
rate per 100.000 residents	0,00	9124,09	313,76	780,28
rate per 100.000 pop. at risk	0,00	3639,90	172,99	363,80
robbery (N=967)				
daytime incidences (N=536)[c]	0	21	1,66	2,90
rate per 100.000 residents	0,00	1895,31	87,09	220,88
rate per 100.000 population at risk	0,00	1290,32	41,31	103,20
night-time incidences (N=428)[d]	0	19	1,33	2,42
rate per 100.000 residents	0,00	1724,14	67,15	205,39
rate per 100.000 pop. at risk	0,00	1652,89	36,27	133,25

[a] zero incidences in 56 (17.3 p.c.) of tracts
[b] zero incidences in 67 (20.7 p.c.) of tracts
[c] zero incidences in 151 (46.7 p.c.) of tracts
[d] zero incidences in 161 (50.8 p.c.) of tracts

Tab. 2. Descriptive statistics of independent variables (Cologne, N=323 census tracts)

	minimum	maximum	mean	std. dev.
Commercial land use (shops, doctor's practices per km², z-stand.)[a]	-0,39	6,96	0,04	0,84
Bars & restaurants per km² [a]	0,00	467,91	17,50	47,26
Distance from city center (meters)	335,77	16741,75	6251,44	3229,67
Population density (population at risk per km²)[a]	43,05	147285,05	12536,64	16448,11
% unmarried persons[a]	26,64	96,81	42,09	8,53
% residents 60yrs and older	0,00	47,64	21,27	7,05
% welfare recipients[a]	0,00	88,68	6,96	8,87

[a] log transformed in regression models

Table 3. Bivariate correlations of dependent and independent variables

		1	2	3	4	5	6	7	8	9	10
1	Assault rate (residents)[a]										
2	Assault rate (pop. at risk)[a]	.824 **									
3	Robbery rate (residents)[a]	.558 **	.294 **								
4	Robbery rate (pop. at risk)[a]	.364 **	.319 **	.871 **							
5	Commercial land use[b]	.179 **	.037	.212 **	.103						
6	Bars & restaurants[b]	.208 **	.052	.230 **	.106	.688 **					
7	Distance from center	-.341 **	-.215 **	-.289 **	-.175 **	-.409 **	-.439 **				
8	Population density[b]	.007	-.090	.064	-.025	.623 **	.688 **	-.477 **			
9	% unmarried persons[b]	.416 **	.373 **	.311 **	.251 **	.299 **	.378 **	-.461 **	.230 **		
10	% residents 60yrs+	-.322 **	-.340 **	-.155 **	-.148 **	.102	-.009	-.052	.194 **	-.619 **	
11	% welfare recipients[b]	.321 **	.418 **	.145 **	.211 **	.072	.126 *	-.160 **	.273 **	.229 **	-.213 **

** p<0.01 * p<0.05 (2-tailed).
[a] square root transformation
[b] log transformation

Tab. 4. WLS-regression models of assault and battery rates (Cologne 1999/2000)

standard. beta-coefficients t-values	daytime		nighttime	
	residents	pop. at risk	residents	pop. at risk
intercept	64.37 2.98 **	24.33 1.97 *	46.21 1.92 ns.	13.23 .94 ns.
block 1 – 'routine activity' variables				
Commercial land use	.227 2.99 **	.159 2.17 *	.176 2.44 *	.108 1.51 ns.
Bars & restaurants	.201 2.19 *	.051 .58 n.s.	.259 2.98 **	.180 2.07 *
Distance from center (meters)	-.381 -5.21 ***	-.220 -3.12 **	-.306 -4.42 ***	-.157 -2.27 *
Population density	-.388 -4.25 ***	-.422 -4.80 ***	-.255 -2.95 **	-.337 -3.90 ***
% unmarried persons	-.082 -.82 ns.	.020 .20 ns.	-.011 -.12 ns.	.099 1.05 ns.
% population aged 60yrs+	-.197 -2.53 *	-.108 -1.44 ns.	-.241 -3.26 ***	-.202 -2.74 **
Block 2 ,deprivation' variable and interactions				
% welfare recipients	.274 5.02 ***	.552 10.55 ***	.187 3.63 ***	.427 8.23 ***
% welfare recip. * bars & restaurants	-.163 -3.32 ***	-.073 -1.54 ns.	-.167 -3.58 ***	-.067 -1.45 ns.
% welfare recip. * population 60yrs+	-.059 -1.12 ns.	-.023 -.56 ns.	-.118 -2.55 *	-.089 -2.12 *
Block 1 – R^2	.210	.107	.302	.212
Block 2 – additional R^2	.094	.248	.074	.165
Total adjusted R^2	.284	.336	.358	.359

*** $p<0.001$ ** $p<0.01$ * $p<0.05$ ns. $p>0.05$
N=323 census tracts; dependent variables are square-root transformed

Tab. 5. WLS-regression models of robbery rates (Cologne 1999/2000)

standard. beta-coefficients *t-values*	daytime		nighttime	
	residents	pop. at risk	residents	Pop. at risk
Intercept	8.34 .47 ns.	0.59 .06 ns.	-12.52 -.84 ns.	-17.42 -1.87 ns.
block 1 – 'routine activity' variables				
Commercial land use	.162 2.02 *	.131 1.55 ns.	.057 .72 ns.	-.032 -.39 ns.
Bars & restaurants	.203 2.10 *	.177 1.74 ns.	.222 2.35 *	.197 1.94 (*)
Distance from center (meters)	-.224 -2.90 **	-.147 -1.82 ns.	-.178 -2.36 *	-.061 -.75 ns.
Population density	-.090 -.94 ns.	-.203 -2.00 *	.007 .08 ns.	-.105 -1.04 ns.
% unmarried persons	.022 .21 ns.	.082 1.16 ns.	.132 1.28 ns.	.271 2.47 *
% population aged 60yrs+	.004 .06 ns.	.101 1.17 ns.	.018 .22 ns.	.115 1.34 ns.
Block 2 ,deprivation' variable and interactions				
% welfare recipients	.083 1.45 ns.	.272 4.50 ***	.027 .48 ns.	.223 3.72 ***
% welfare recip. * bars & restaurants	-.134 -2.29 *	.012 .22 ns.	-.088 -1.73 ns.	.040 .74 ns.
% welfare recip. * population 60yrs+	-.064 -1.24 ns.	-.051 -.93 ns.	-.006 -.12 ns.	.040 .74 ns.
Block 1 – R^2	.199	.080	.250	.115
Block 2 – additional R^2	.028	.062	.008	.039
Total adjusted R^2	.208	.117	.237	.129

*** p<0.001 ** p<0.01 * p<0.05 ns. p>0.05
N=323 census tracts; dependent variables are square-root transformed

Figure 1a. Assault and battery rates per residents and per population at risk in downtown and other areas (Cologne, 1999/2000)

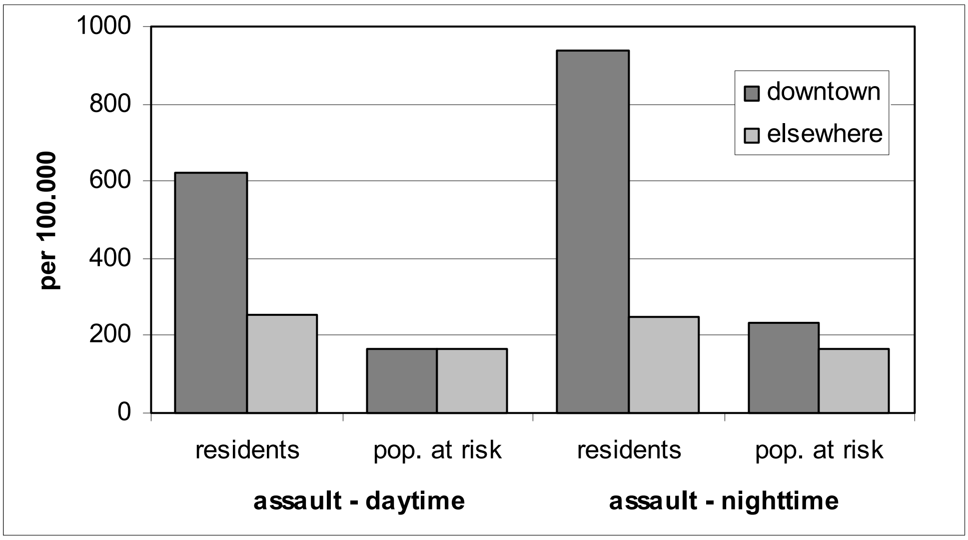
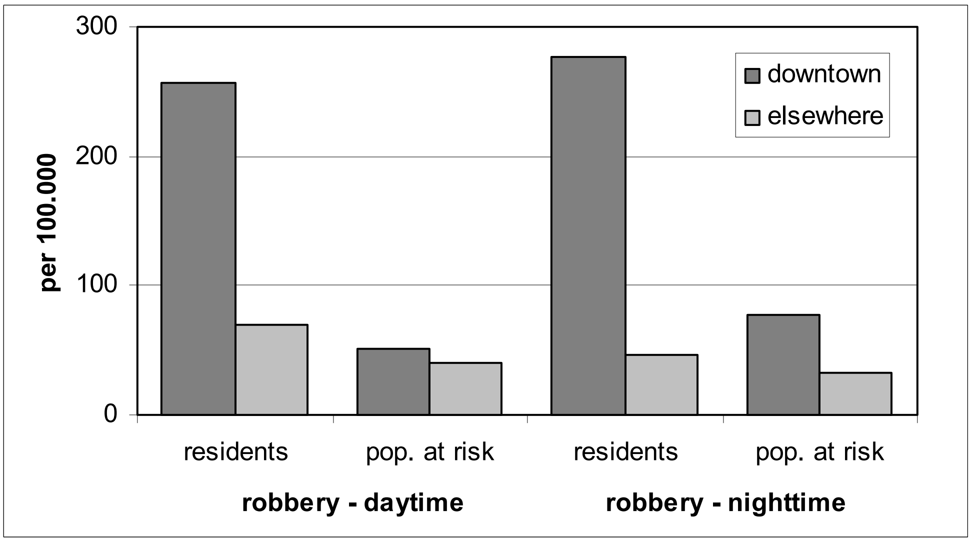
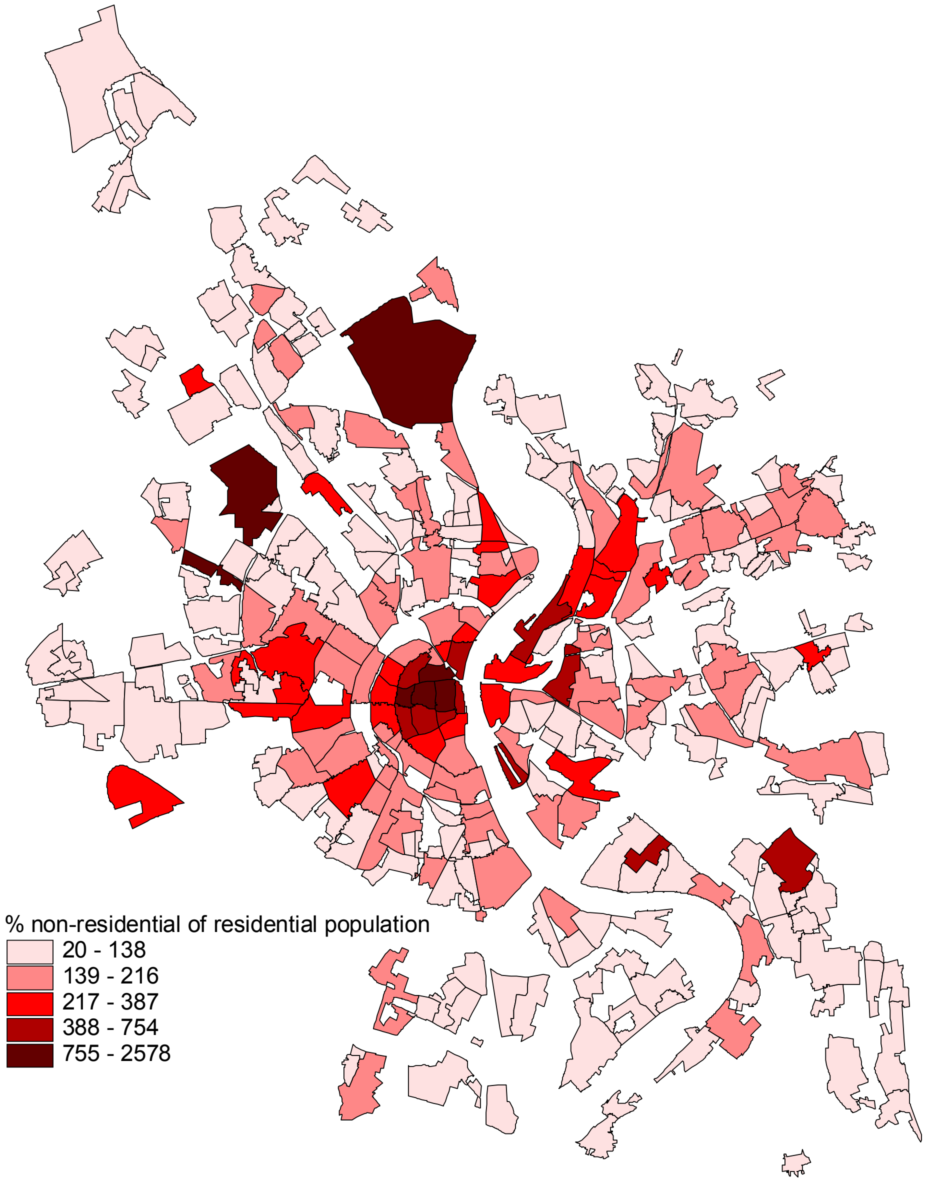


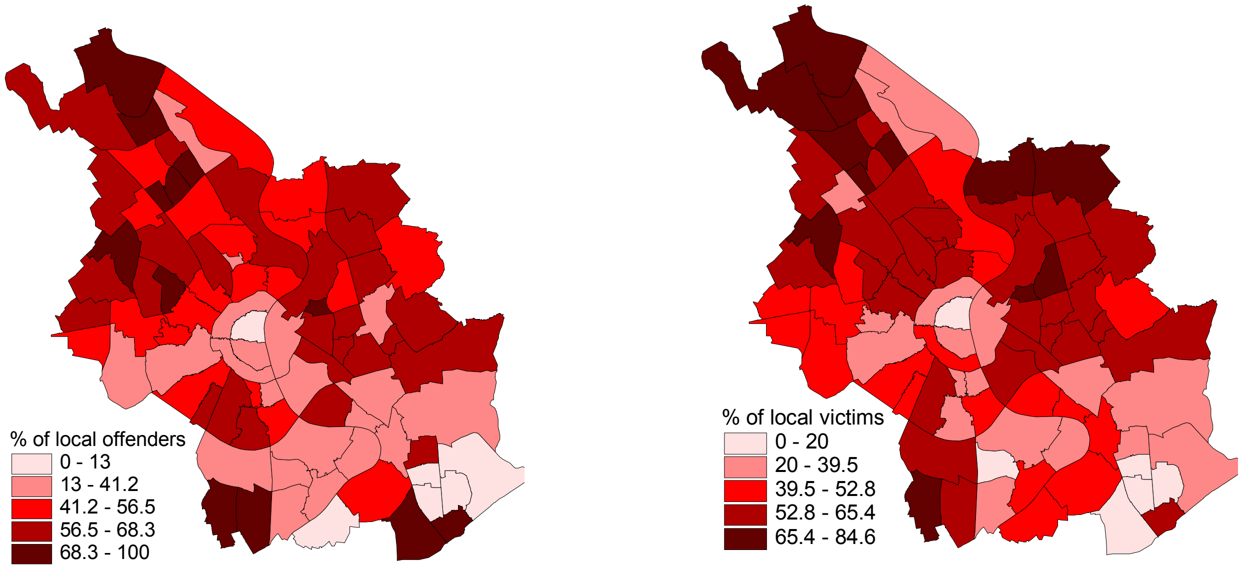
Figure 1b. Robbery rates per residents and per population at risk in downtown and other areas (Cologne, 1999/2000)



Map 1. Percentage non-residential population of residential population (Cologne 1997/1998, N=309 census tracts, tracts with < 100 residents excluded)



Maps 2a (left) and 2b (right). Percentage of offenders (left) and victims (right) of violence who are residents in the area where the crime happened (Cologne 1999)



(N=85 large spatial units with N=5281 victims and N=3813 offenders)

Maps 3a (left) and 3b (right). Risk surfaces of violent crimes using residential population (left) or population at risk (right) as denominator (Cologne, 1999/2000, dual kernel density estimation in CrimeStat 2.0)