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Associations of neighborhood disadvantage and offender concentration with criminal behavior: Between-within analysis in Finnish registry data

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ABSTRACT

The association between neighborhood disadvantage and crime has been extensively studied, but most studies have relied on cross-sectional data and have been unable to separate potential effects of the neighborhood from selection effects. We examined how neighborhood disadvantage and offender concentration are associated with criminal behavior while accounting for selection effects due to unobserved time-invariant characteristics of the individuals. We used a registry-based longitudinal dataset that included all children aged 0–14 living in Finland at the end of year 2000 with follow-up until the end of 2017 for criminal offences committed at ages 18–31 years ($n = 510{,}189$). Using multilevel logistic regression with a between-within approach we examined whether neighborhoods differed in criminal behavior and whether within-individual changes in neighborhood disadvantage and offender concentration were associated with within-individual changes in criminal behavior. Our results indicated strong associations of most measures of neighborhood disadvantage and offender concentration with criminal behavior between individuals. The within-individual estimates accounting for selection related to unobserved individual characteristics were mostly non-significant with the exception of higher neighborhood disadvantage being associated with increased risk for violent crimes. Our findings suggest that criminal behavior is better explained by individual characteristics than by causal effects of neighborhoods.

1. Introduction

Social patterns in crime and delinquent behavior have long been recognized and examined. Many earlier studies have noted that criminal behavior varies according to sex, age, and socioeconomic position so that men, young adults, and those with low education and in low income occupations are more likely to commit crimes (e.g. Braithwaite, 1981; Green, 1970). According to the classic strain theory in criminology, low socioeconomic status causes frustration and strain which lead individuals to commit crimes (Merton, 1938). While more recent findings have pointed towards social selection as a mechanism explaining the association between low socioeconomic status and criminal behavior, it is likely that these associations are at least partially causal (Aaltonen, Kivivuori, & Martikainen, 2011; B. R. E. Wright, Caspi, Moffitt, & Silva, 1999). Moreover, the effect of social selection may be even more pronounced in egalitarian states such as Finland and the other Nordic countries, where social policies function to narrow socioeconomic differences possibly leading to other individual traits to have a larger overall effect on criminal behavior (Savolainen, Paananen, Merikukka, Aaltonen, & Gissler, 2013).

As an integral part of social patterning, criminologists have also examined, and attempted to explain, differences in crime rates between neighborhoods for the better part of the last century (Blau & Blau, 1982; Boggs, 1965; Shaw & McKay, 1942). The issue of social causation versus social selection is also debated within the literature of neighborhood effects on criminal behavior – in other words, are differences in criminality between neighborhoods caused by neighborhood characteristics or do people involved in, or at risk of, criminal behavior self-select to certain types of neighborhoods with a higher likelihood than to others? Unfortunately, much of the neighborhood level research on criminal behavior has been cross-sectional (Kubrin & Weitzer, 2003). Importantly, longitudinal studies that utilize more advanced statistical methods have been called for in the field of neighborhood effects research beyond criminology, for example in relation to the potential health effects of neighborhoods (Diez Roux & Mair, 2010; Hipp & Wo, 2015; Subramanian, 2004). Such analyses can better inform whether

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differences in criminal behavior between neighborhoods are more likely to be due to social causation or social selection. Only few longitudinal studies on the association between neighborhood characteristics and criminal behavior have been conducted, and they have suggested only modest effects of social causation (Kubrin & Weitzer, 2003). More recent studies on neighborhood disadvantage and crime have reported somewhat mixed results and have highlighted the need for more longitudinal studies on the topic (Bonomi, Trabert, Anderson, Kernic, & Holt, 2014; Hipp & Wickes, 2017).

Furthermore, the bulk of the evidence on neighborhood effects on criminal behavior is based on findings from the US with relatively few studies being conducted elsewhere (Sampson, Morenoff, & Gannon-Rowley, 2002). Studies from Europe have even yielded somewhat contradictory results (Bruinsma, Pauwels, Weerman, & Bernasco, 2013). It is therefore important to further examine the association between neighborhood disadvantage and crime using longitudinal data from societies with different social, welfare, and educational policies as well as judicial systems. In the present study, we utilize between-within analysis using official registry data with a long follow-up time to examine changes in criminal offending among young adults in Finland when they move between neighborhoods or the characteristics of their neighborhoods change over time. The between-within analyses allow us to estimate the associations between criminal behavior and neighborhood disadvantage using individual as their own controls and therefore accounting for unobserved individual-level time-invariant characteristics which may confound the association between neighborhood characteristics and criminal offending.

1.1. Prior literature

Differences in crime rates have been observed at various socio-geographical levels ranging from the country level (Ousey, 2000) to neighborhoods to residential blocks (Bernasco & Block, 2011) with some studies focusing on crime location and others on offender residence. For practical reasons, neighborhoods are often defined using census tracts or blocks. Census data allow for consistent measurements of neighborhoods and their characteristics at different time points. Studies relying on census tracts have linked neighborhood disadvantage, as measured by the percentage of households living under the poverty threshold, with various types of crime from burglaries (Nobles, Ward, & Tillyer, 2016) to homicides (Kawachi, Kennedy, & Wilkinson, 1999). Other aspects of neighborhoods that are often used as indicators of disadvantage are housing tenure and unemployment. Findings from the US suggest that the share of renters in an area is positively associated with crime rates in low-income areas, but not in affluent areas (Hegerty, 2017). Similarly, a study from the UK concluded that while housing tenure was associated with crime rates, it was outweighed by the effects of income deprivation and number of alcohol outlets in an area (Livingston, Kearns, & Bannister, 2014). Differences in criminal behavior of residents between neighborhoods may also be due to social interactions with other residents who have committed criminal offences (Glaseser, Sacerdote, & Scheinkman, 1996). Indeed, a British study found offender concentration in a neighborhood to be positively associated with property and violent crimes committed by the residents (Kearns, Livingston, Galster, & Bannister, 2019). Similar findings in US-based data suggested that the associations may be offence specific among youths– that is, social interactions with offenders of certain types of crime are more strongly associated with later offences of similar crimes than with other types of offences (Mennis & Harris, 2011).

Besides just assessing associations, criminologists have always attempted to uncover the causal mechanisms behind the associations. Some of the earlier empirical attempts were motivated by the theory of social disorganization. According to the theory, characteristics of neighborhoods are more significant predictors of criminal behavior than are individual characteristics (Shaw & McKay, 1942). In essence, low socioeconomic status, and high residential mobility and ethnic heterogeneity of a neighborhood are thought to cause social disorganization, which increases the risk of criminal behavior of its residents. The theory has since evolved several times, with the latest refinement being the concept of collective efficacy (Sampson et al., 2002; Sampson, Raudenbush, & Earls, 1997). Collective efficacy is seen as a mediator between neighborhood disadvantage and criminal behavior. It refers to the collective sense of residents being able to enforce informal social control over each other. That is, collective efficacy is thought to have an effect on how well residents can prevent others from acting in delinquent ways and possibly intervene to stop such actions. Without proper resources neighborhoods lack collective efficacy, and thus informal social control, leading to increase in crime. Indeed, collective efficacy at neighborhood level appears to be an important factor in explaining the association between neighborhood disadvantage and crime. Still, neighborhood disadvantage remains a significant predictor of neighborhood level crime even after accounting for collective efficacy at least in US based studies (Sampson et al., 1997; Sampson, Morenoff, & Earls, 1999). Similar results have also been reported in a Swedish study (Sampson & Wikström, 2008), although more recent studies from Nordic countries refute these findings, instead showing that neighborhood disadvantage is no longer associated with violent crime after accounting for collective efficacy (Danielsson, 2019; Gerell & Kronkvist, 2016).

Studies on neighborhood disadvantage and crime have predominantly been conducted in the US (Sampson et al., 2002). It is therefore not well understood how, and to what extent, the associations exist in other countries, even though researchers argue that differences between neighborhoods are universal (Sampson, 2013). Nordic countries, for example, are much more homogenous and equal societies compared to the US. Using the Gini coefficient, Nordic countries have been consistently ranked among the most equal societies in the world (World Bank, 2021). The US, on the other hand, is among the more unequal societies. Thus, the range of differences between neighborhoods is far narrower and neighborhood disadvantage less extreme in the Nordic countries as compared to the US. As a consequence, the possible effects of neighborhood disadvantage might not be as overt. Findings from studies using Swedish data have supported this view (Brännström, 2004; Sariaslan et al., 2013). Similarly, a thorough examination of how social disorganization theories apply in the Dutch context found mixed support for the theories (Bruinsma et al., 2013). The results corroborated the traditional theory's assumptions of socioeconomic status and residential mobility of the neighborhood being linked with criminal behavior but results on the heterogeneity of ethnic composition were non-significant. Furthermore, collective efficacy was also not associated with criminal behavior in the Dutch study (Bruinsma et al., 2013). Importantly, while the variance in neighborhood socioeconomic status may be smaller in Europe than in the US, it does not rule out differences in criminal behavior (Aaltonen, Kivivuori, Martikainen, & Salmi, 2012; Savolainen, Bjarnason, & Hughes, 2013).

In general, studies of neighborhood effects have mostly been conducted using cross-sectional data and the need for longitudinal studies has been underlined repeatedly (Diez Roux & Mair, 2010; Hipp & Wo, 2015; Subramanian, 2004). Importantly, the use of longitudinal data allows for study designs that can better shed light on whether findings on the association between neighborhood characteristics and criminal behavior are likely to be causal or whether they arise because of individuals self-selecting to certain neighborhoods (Kirk & Laub, 2010). Studies utilizing longitudinal data have yielded somewhat mixed findings. Results based on the Moving to Opportunity social experiment – a study of 4600 low-income families in the United States – suggested that the effect of neighborhood disadvantage on criminal behavior may be gender specific among youth so that overall criminal behavior of girls who moved to affluent areas would decrease, whereas property offences committed by boys would increase (Kling, Ludwig, & Katz, 2005). Neighborhood effect studies on other topics have often used longitudinal datasets and study designs that take advantage of such data. Jokela, for example, showed that using individuals as their own controls is a viable way of establishing a credible connection between neighborhood characteristics and health related outcomes (Jokela, 2014, 2015). Such within individual designs have later been used on neighborhood effects of psychological well-being as well (Airaksinen et al., 2015). Unfortunately, studies utilizing repeated measurements from the same individuals are scarce in criminology. More often the longitudinal studies on neighborhood effects on crime use repeated cross-sectional data that only allow for examination of changes at area level, but not at individual level.

Therefore, in this study, we examined associations of neighborhood disadvantage and offender concentration with criminal behavior in Finland using longitudinal individual level registry-based data. We used multiple indicators for neighborhood disadvantage in order to examine whether some of them might be more relevant than others. We expected increased neighborhood disadvantage, across all indicators of disadvantage, as well as offender concentration to be linked with increased criminal behavior. Further, by using between-within analysis (Carlin, Gurrin, Sterne, Morley, & Dwyer, 2005; Sariaslan et al., 2013), which enables decomposition of the exposure-outcome association into between- and within-subject components, we were able to examine how participants' criminal behavior varied over time as they lived in neighborhoods of varying disadvantage and offender concentration, therefore accounting for the unobserved individual characteristics by which self-selection to neighborhoods occur. Again, we expected participants' criminal behavior to increase as they lived in more disadvantaged neighborhoods and in neighborhoods with higher offender concentration.

2. Methods

2.1. Study design and participants

The participants for this study came from the EKSY-Children dataset. The EKSY-Children is a registry-based dataset of all children aged 0–14 living in Finland at the end of year 2000 ($n = 936{,}333$) who were followed annually until the end of 2017, and is further supplemented with data on the biological parents ($n = 1{,}046{,}549$) and grandparents ($n = 1{,}195{,}624$) of the children. The dataset includes yearly individual-level information such as age, sex, educational attainment, income, labor market status, and place of residence at postal code level. Besides basic demographic variables, the dataset is linked with police records for being suspected of crimes. We limited our analytic sample to participants aged 18 years or older. Within this framework the age in our sample ranged from 18 to 31. Importantly, we also limited our sample to those living in cities with more than 100,000 residents at any time during the follow-up, and further to postal code areas with at least 100 residents. This was done because postal code areas in rural parts of Finland are relatively large in size and thus may not represent neighborhoods in the same way as in more urban areas. It has also been pointed out that the social disorganization theory may not even generalize to rural areas (Kaylen & Pridemore, 2011). While there are only nine cities with over 100,000 residents (Helsinki, Espoo (including Kauniainen), Tampere, Vantaa, Oulu, Turku, Jyväskylä, Kuopio, and Lahti) in Finland, the total number of residents from those cities make up roughly 40% of the overall population of Finland. See Table 1 for comparison between all postal code areas and those included in the analysis. To get a further sense how the areas included in our analysis differed from the excluded areas in regard to areas that can be though as neighborhoods, we extracted the surface areas and population densities from the Statistic Finland database on postal areas (Statistics Finland, 2021). In 2017 the median surface areas of the postal code areas were 4.4km^2 and 60.4km^2, and median population densities were 971.2 per km^2 and 8.1 per km^2, for area included in our analysis and those excluded, respectively. Our final analysis sample consisted of 510,189 participants with 2,927,510 annual person-observations.

Table 1
Descriptive statistics for postal code areas in 2017.

	All postal code areas	Sample postal code
	Mean (SD)	Mean (SD)
Population	1548 (2033)	3507 (2981)
Age	42.2 (4.7)	39 (3.8)
Unemployment (%)	10.0 (4.3)	10.6 (4.2)
Rental (%)	14.0 (13.8)	27.5 (18.8)
Low education (%)	14.0 (4.8)	12.6 (5.5)
Low income (%)	18.1 (5.7)	18.2 (6.0)
Suspected of…		
Other crime (%)	1.5 (0.7)	1.4 (0.6)
Violent crime (%)	0.5 (0.3)	0.4 (0.2)
Property crime (%)	0.7 (0.4)	0.8 (0.4)

2.2. Measurements of neighborhood level predictors

Unfortunately, the Statistic Finland database on postal code areas does not cover majority the years included in our follow-up. Therefore, the neighborhood level predictors were aggregated from the overall dataset at postal code level using all the data available from the EKSY-Children dataset, including the children and their parents and grandparents for the postal code area located in cities with over 100,000 residents. Altogether, our analyses included 380 unique neighborhoods defined by postal code areas out of the total 3027 postal code areas in Finland. Neighborhood level offender concentration variables for each year were obtained by calculating the proportion of residents aged 15 to 65 who had been suspected of various types of crimes during the previous year. Had we not used the offender concentration from the previous year, our results would have been biased as our outcome of an individual being suspected of a crime would have contributed directly to our exposure. Further, to avoid bias due to older cohorts' different educational structure and retirement, we aggregated all predictors other than offender concentration using information on residents aged between 30 and 65. The predictors used in this study were: 1) percentage of people with low income (lowest quintile), 2) percentage of residents with basic education, 3) unemployment rate, 4) percentage of residents living in rental apartments, 5) percentage of residents suspected of violent crimes, 6) percentage of residents suspected of crimes against property, and 7) percentage of residents suspected of other crimes (excluding traffic violations). As all neighborhood level predictors were measured as percentages, they ranged from 0 to 100. Furthermore, as our measures of disadvantage were relatively highly correlated (range: 0.05–0.85) we also examined the association between neighborhood characteristics and criminal behavior using a compound measure for disadvantage and offender concentration. We used principal component analysis and retained the first component (Lalloué et al., 2013; Messer et al., 2006) that we then used as the exposure measure. To account for possible non-linear association between criminal behavior and the neighborhood level predictors, we further categorized the predictors to deciles so that the first decile represented the least disadvantaged neighborhood and the tenth decile the most disadvantaged neighborhood. In the analysis we used dummy coded variables for neighborhood disadvantage deciles for each indicator. It is important to note that for a given individual, a change in neighborhood decile could be due to the neighborhood itself changing in time or due to the individual moving to a different neighborhood.

2.3. Measurement of individual criminal behavior outcomes

The outcome of interest was whether participants were suspected of crimes during a given year. In order to assess whether area level characteristics were differently associated with being suspected of different types of crimes, we used three distinct binary outcome measures: 1) being suspected of violent crimes (e.g., petty assault, assault, causing bodily injury), 2) being suspected of crimes against property (e.g., petty larceny, theft, fraud, property damage), and 3) being suspected of other crimes (e.g., endangering road safety, offences against other acts and decrees). We excluded traffic infractions, that account for the majority of other crimes, because they are relatively minor offences whose measurement changes considerably over time due to adoption of automatic traffic surveillance. Traffic infractions accounted for nearly 79% of crimes in the "other crimes" category.

2.4. Measurement of other individual level covariates

Criminal behavior is highly correlated with age, sex, and educational attainment, which are also likely to be related to place of residence. Therefore, we included them as covariates in the analyses. Educational attainment was measured as highest held degree and categorized into five groups (the corresponding ISCED-2011 codes in parentheses): 1) lower secondary school (2), 2) trade school or equivalent (3), 3) high school (3), 4) bachelor's degree or equivalent (5/6) and 5) master's or doctoral degree (7/8). As educational attainment could not decrease over time, we used the highest held degree for each participant over all time points. Labor market status of each participant was also used as a covariate, and it was divided into four categories: 1) employed, 2) unemployed, 3) student and 4) other (conscript, work disability pension, other). Age and labor market status were time-varying variables measured at the end of each year. Labor market status was also dummy coded for the analyses.

2.5. Statistical analysis

We had repeated measures data so that measurements for each year (level 1) were nested within individuals (level 2) who were cross-classified to neighborhoods (level 3). With such a large data and rather complex data structure, it proved to be computationally unfeasible to model the association on three levels with cross-classification. Therefore, we first examined the clustering of criminal behavior between neighborhoods by pooling the data for each participant and year so that our data was on two levels – observations on level 1 and postal code on level 2 – and using the latent response formulation in calculating the intra class correlations (ICC) to quantify the clustering (Austin & Merlo, 2017). For our main analysis we modelled the association between neighborhood characteristics and criminal behavior using multilevel logistic regression models on two levels – year on level 1 and individuals on level 2. Instead of estimating separate random- and fixed-effects models we chose to use the between-within approach (Austin & Merlo, 2017; Sjölander, Lichtenstein, Larsson, & Pawitan, 2013). In practice the between-within analysis was conducted by including the individual-level mean neighborhood disadvantage in the model on level 2 and including the yearly deviations from this mean on level 1. This enabled us to simultaneously estimate the effects of neighborhood characteristics on criminal behavior between individuals (level 2) accounting for observed confounders but also those effects within individuals (level 1) accounting for all unobserved time-invariant and observed time variant confounders. These estimates are reported as odds ratios.

The main analysis was conducted separately for each neighborhood-level predictor, including age and sex as covariates. We also conducted three sensitivity analyses. First, we repeated our main analysis, but also included educational attainment and labor market status as covariates to examine whether they explained any of the possible associations from our main analysis. Second, we ran sex-stratified analyses. As vast majority of crimes are conducted by men (Rowe, Vazsonyi, & Flannery, 1995), the association between neighborhood disadvantage and criminal behavior could well differ between sexes. Lastly, we also examined whether childhood neighborhood disadvantage moderates the association between neighborhood disadvantage and criminal behavior. For this, we computed the mean compound neighborhood disadvantage for each individual when they were aged 7 to 17 years old. We then divided that measure into quartiles and ran the main analysis again stratifying by those quartiles.

3. Results

Descriptive statistics are shown in Table 2. Note the differences in the distributions of neighborhood offender concentration. The distributions of both violent crime offender concentration and property crime offender concentration were rather narrow. The mean for violent crime offender concentration was 0.52 (SD 0.25) and the mean for property crime offender concentration was 0.94 (SD 0.43). Range for violent crime offender concentration was 0.03–5.74, and 0.03–12.84 for property crime offender concentration. The mean for other crime offender concentration was 1.48 (SD 0.47) with a range from 0.18 to 13.85 The distribution of years lived in neighborhoods of varying disadvantage by decile for each indicator are shown in Table 3. The crude neighborhood ICCs for being suspected of violent crimes, property crimes, and other crimes, were 0.06, 0.07, and 0.04, respectively.

The results for the between-within analyses are shown in Figs. 1 and 2. Nearly all between-individual associations of neighborhood indicators with criminal behavior related to violent, property, or other crimes increased as neighborhood disadvantage and offender concentration increased. For the proportion of residents living in rental housing, the association grew for the first few deciles but remained stable for the rest. The strongest associations were found between the neighborhood offender concentration of violent or property crimes and being suspected of property crimes – the odds for individuals being suspected of property crimes in neighborhoods with the highest offender concentration were up to 37-fold compared to those living in neighborhoods with the lowest offender concentration.

Table 2
Descriptive statistics of the 2,927,510 person-observations from 510,189 unique participants.

	Total *n* (%)	Mean (SD)	Within-person SD
Sex			
Male	244,596 (48)		
Female	265,593 (52)		
Age		22.67 (3.3)	2.62
Education			
Lower secondary school	13,208 (3)		
Trade school	80,800 (16)		
High school	290,139 (56)		
Bachelor's degree or equivalent	88,056 (17)		
Master's/doctoral degree	37,986 (7)		
Labor market status[a]			
Employed	322,695 (63)		
Unemployed	41,626 (8)		
Student	110,005 (22)		
Other	35,863 (7)		
Have been suspected of…			
Property crimes	22,733 (4)		
Violent crimes	15,925 (3)		
Other crimes	37,861 (7)		
Postal code area characteristics			
% Unemployment		12.13 (4.59)	2.69
% Living rental		35.10 (13.46)	8.63
% with low education		15.36 (6.23)	3.60
% with low income		18.13 (6.12)	4.06
% suspected of violent crimes		0.55 (0.25)	0.19
% suspected of property crimes		0.96 (0.43)	0.33
% suspected of other crimes		1.38 (0.54)	0.45

[a] Labor market status from the last observation for each participant.

Table 3
Mean percentage over all participants of the years lived in each decile for each indicator during follow-up

Decile	Unemployment	Rental	Low education	Low income	Violent crime	Property crime	Other crimes	Index
1	5	1	6	4	7	6	7	10
2	7	3	12	5	8	8	9	10
3	8	5	12	7	10	9	10	10
4	9	7	10	8	10	10	11	10
5	9	9	9	10	10	11	11	10
6	11	10	9	9	12	12	12	10
7	12	14	10	13	11	12	11	10
8	13	19	8	14	11	12	11	10
9	14	19	12	13	11	12	11	10
10	12	13	12	15	10	10	7	10

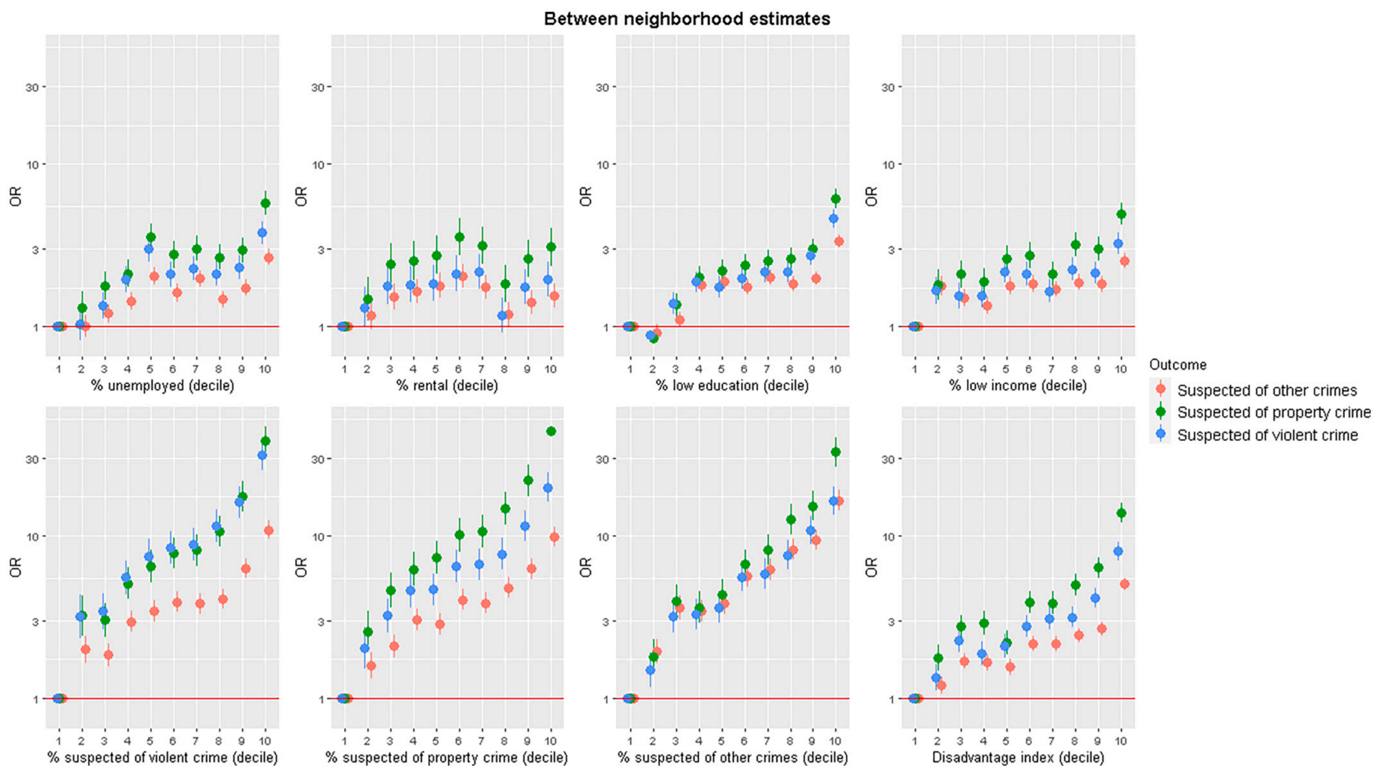

Fig. 1. Between individual estimates for neighborhood disadvantage and offender concentration as deciles and criminal behavior, adjusted for age and sex. Decile 1 is the least disadvantaged neighborhood and decile 10 is the most disadvantaged neighborhood. Note that odd ratios are presented on a logarithmic scale.

As expected, the within-individual associations were much weaker than between-individual associations (Fig. 2). Associations between neighborhood disadvantage and being suspected of crimes against property or other crimes were mostly non-significant. Associations for being suspected of violent crimes were significant for the following neighborhood disadvantage indicator: proportion of residents living in rental housing, and proportion of residents with low income. The estimates for both between- and within-individual results are shown in Supplementary Tables A & B.

Further adjusting the models for educational attainment and labor market status attenuated both the between- and within-individual estimates, but not as much as to change any inference drawn from the results (Supplementary Figs. A and B). The sex stratified analysis also did not reveal any large discrepancies in the between-individual association between sexes (Supplementary Figs. C and D). In the within-individual association the confidence intervals were expectedly much larger for women rendering some of the associations non-significant (Supplementary Figs. E and F). The results for examining whether childhood neighborhood disadvantage moderate the associations are shown in Supplementary Figs. G through L, no consistent patterns emerge on how childhood neighborhood context would moderate the association between neighborhood disadvantage and criminal behavior.

4. Discussion

The neighborhood effect research on criminal behavior has predominantly been based on cross-sectional data, with much of the literature originating from the US. In this study we examined whether neighborhood disadvantage and offender concentration are associated with criminal behavior in Finland using longitudinal individual level registry data. Our results suggest differences in criminal behavior between individuals living in neighborhoods of varying disadvantage in Finland, but they only lend weak support for neighborhood disadvantage itself as having an effect on criminal behavior.

In our results for differences between individuals for all the neighborhood disadvantage measures living in a neighborhood with higher disadvantage or higher offender concentration was associated with higher odds of being suspected of violent, property, or other crimes. The most pronounced example being the association between neighborhood offender concentration – living in neighborhoods with the highest

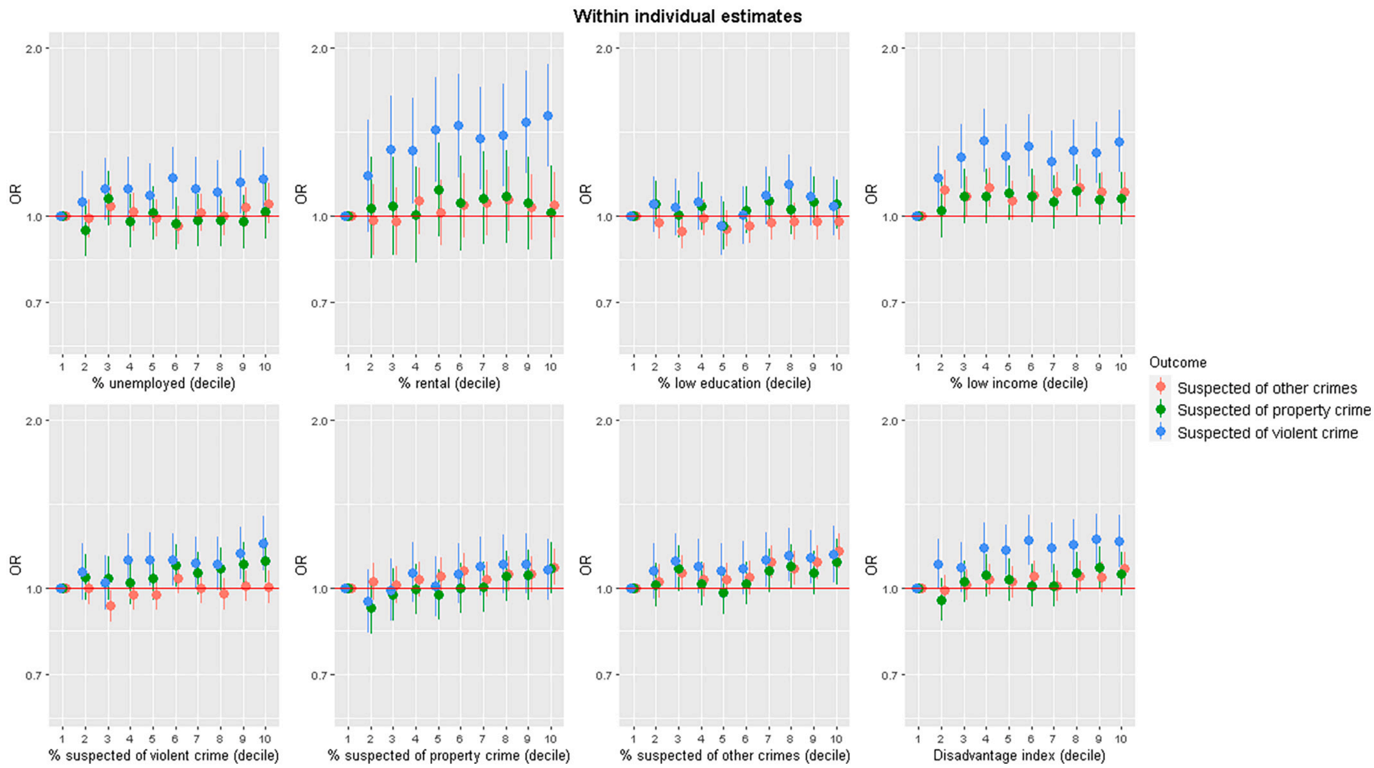

Fig. 2. Within individual estimates for neighborhood disadvantage and offender concentration as deciles and criminal behavior, adjusted for age and sex. Decile 1 is the least disadvantaged neighborhood and decile 10 is the most disadvantaged neighborhood. Note that odd ratios are presented on a logarithmic scale.

offender concentration was associated with up to 37 times higher odds of being suspected of property crimes compared to living in neighborhoods with the lowest offender concentration.

Even though our results suggest that there are large relative differences between neighborhoods in criminal behavior, the results should be interpreted with a reference to the low prevalence of actual offenders in the neighborhoods. For example, in neighborhoods with the lowest level of unemployment, roughly 0.2% of residents had been suspected of violent crimes during a given year, and in neighborhoods with highest level of unemployment, the proportion was 0.5%.

The inference for a potentially causal relationship between neighborhood disadvantage and criminal behavior is clearer in the within-individual analyses. For all neighborhood disadvantage measures, except for neighborhoods where higher proportion of residents had low income or were suspected of violent or other crimes, increase in neighborhood disadvantage was not associated with higher odds for being suspected of crimes against property or other crimes. The within-individual association for the proportion of residents with low income showed roughly 10% higher odds for being suspected of other crimes when living in neighborhoods with the highest offender concentration compared to living in the neighborhoods with the lowest offender concentration. Higher proportion of resident having been suspected of violent crimes was associated with 10–15% increase for being suspected of property crimes when living in the most disadvantaged neighborhoods. Similarly, higher proportion of resident having been suspected of other crimes was associated with 10–15% increase for being other of property crimes when living in the most disadvantaged neighborhoods.

Within-individual associations between neighborhood disadvantage and violent crimes were more pronounced. Living in neighborhoods where larger proportion residents were living in rental housing or had low income was associated with increased risk for being suspected of violent crimes. For the rental housing indicator, the odds were up to 50% higher when living in the most disadvantaged neighborhoods compared to living in the least disadvantaged neighborhoods, and for low-income indicator the odds were up to 35% higher. Importantly, however, there was no clear gradient in the increase of risk when moving to more disadvantaged neighborhood deciles. Rather, living in the first, second or third least disadvantaged neighborhood deciles seemed to be associated with a very small risk for being suspected of violent crime, and living in any of the other neighborhood deciles was associated with roughly a 35–50% higher risk, irrespective of the level of disadvantage. Still, even though these odds were much lower compared to the between-individual estimates, such associations may prove to have significant real world consequences at population level and even for an individual (Funder & Ozer, 2019).

Although we observed in the within-individual analysis that higher neighborhood disadvantage was associated with higher risk for being suspected of crimes, especially violent crimes, our research design does not offer ways to identify mechanisms driving those associations. Childhood neighborhood conditions have been suggested to have lasting effects on an individual (Glass & Bilal, 2016; Wodtke, Harding, & Elwert, 2011). However, when we examined whether childhood neighborhood disadvantage might act as a moderating factor in the observed within-individual associations, we found no consistent results that would support this view.

It is important to interpret our findings in light of the rather small variance (ICC) in criminal behavior between neighborhoods – similar to those in Sweden, for example (Sariaslan et al., 2013). With a large sample size and small variance between neighborhoods in the outcome, even minor associations are easily found to be statistically significant (Merlo, Wagner, Austin, Subramanian, & Leckie, 2018). Thus, our results suggest that neighborhood context may not be very relevant in explaining differences in criminal behavior in Finland. This is in line with the findings of a study based on Swedish data that found neighborhood deprivation not to be as important as familial factors in explaining criminal behavior and substance abuse (Sariaslan et al., 2013).

Some European studies on neighborhood effects on criminal behavior have also applied methods similar to ours. For example, two Scottish studies concluded that the concentration of recent offenders in an area was linked with subsequent violent and property crimes in that area (Kearns et al., 2019; Livingston, Galster, Kearns, & Bannister, 2014) both congruent with our results. Similar conclusions have been drawn from two different Danish studies that used longitudinal data (Damm & Dustmann, 2014; Rotger & Galster, 2019). While some U.S. based studies using longitudinal data have also linked offender concentration or peer delinquency with increase in criminal behavior (Mennis & Harris, 2011; K. A. Wright, Kim, Chassin, Losoya, & Piquero, 2014), they have not examined within-individual associations and they have also been limited to examining youth recidivism. Many other studies have shown that neighborhood disadvantage, as measured by a wide array of indicators, is associated with increased crime rates, but the these have commonly only utilized cross-sectional data (Andresen, 2006; Hegerty, 2017; Sun, Triplett, & Gainey, 2004).

On a broader level, our findings are also congruent with criminological theories. For example, the social disorganization theory posits that neighborhoods of high disadvantage tend to have high levels of crime (Sampson et al., 2002), which is exactly what we observed in our between individual analysis. Moreover, the result that individuals were in higher risk to be suspected of violent crimes when living higher disadvantaged neighborhoods corroborates this view. Similar results have been reported in a recent study (Chamberlain & Hipp, 2015) that also emphasized the how the disadvantage of surrounding neighborhoods may exacerbate the effect on violent crime.

Overall, our between individual analyses showed an association between neighborhood disadvantage and risk for criminal behavior, but taken together the within-individual analyses did not show a clearly elevated risk of criminal behavior when residing in disadvantaged neighborhoods, except for violent offending. None of our sensitivity analysis changed the overall interpretation of the results. This suggests that differences in criminal behavior between neighborhoods may be more due to social selection rather than social causation. In other words, people with an elevated risk of criminal behavior may be self-selected to certain types of neighborhoods, thus creating the observed association between neighborhood disadvantage and criminality, rather than neighborhood characteristics being the cause of the differences. Despite the strengths of our data and study design, identifying the factors driving the selection process was out of the scope of this study.

4.1. Limitations

Even with the strengths of comprehensive registry data and the between-within design, our study has some important limitations to be considered. First, inherent to all neighborhood effect studies is the issue of defining a neighborhood. The subjective experience of a neighborhood might not be equivalent to the objective measures used to define neighborhoods (Kirk & Laub, 2010). Thus, the actual effect of experienced neighborhood characteristics on the behavior of the residents might differ from the observed. Second, we were only able to measure neighborhood disadvantage through objective measures such as income, unemployment and offender concentration. We could not incorporate collective efficacy into the study to examine if it is as relevant in reducing criminal behavior in Finland as it has been shown to be in the US (Hipp & Wo, 2015; Sampson et al., 1997), although recent evidence from Nordic countries suggests that they may be (Danielsson, 2019; Gerell & Kronkvist, 2016). An aspect we also had to omit from this study due to computational limitations was the effect of surrounding neighborhoods. Earlier studies have suggested that crime level of neighborhoods may be affected by the characteristics of other neighborhoods (Chamberlain & Hipp, 2015). Similarly, at an individual level we were not able to control for the distance between consecutive neighborhoods a person lives in even though that could affect how changes in neighborhood disadvantage reflect on criminal behavior. If a person moves to a less disadvantaged neighborhood close by, they might retain their old social relationships, which in turn could negate any changes brought by the change in neighborhoods. Likewise, due the nature of our data, we might have omitted some important time varying individual level variables that could have been related to criminal behavior, thus introducing bias to our results. Indirect effects of neighborhood disadvantage, for example familial factors, could also have potentially biased the observed within-individual associations towards null. Bias could also have been introduced to our results because some individuals might have contributed to both the predictor (having been suspected of crimes during the previous year) and the outcome (having been suspected of crimes during the year). Closely related to this point is the fact that we did not have data on where the actual crimes the residents were suspected of were committed. We only had data on whether people were suspected of crimes or not. Besides our data, also our study design had limitations. Even though our approach allowed us to examine how an individual's criminal behavior changed as their neighborhood changed, it does not capture the possible effect constantly living in a disadvantaged neighborhood may have on criminal behavior. Another issue is reverse causation. As our outcome and exposure were measured from the same time point, it may be that changes in where an individual lives are actually due their criminal behavior rather than vice versa.

5. Conclusions

Using longitudinal registry data from Finland, a country with generous welfare state provisions and a relatively small urban segregation, we showed that neighborhood disadvantage and offender concentration are not key factors in causing criminal behavior. Rather, our results suggest that differences in criminal behavior between individuals living in neighborhoods of varying disadvantage and offender concentration are mostly due to social selection rather than social causation, with the notable exception of higher neighborhood disadvantage increasing the risk for violent crimes. Studies that utilize more detailed data on the social interactions between residents may be needed to explain the latter finding, and to elucidate the mechanisms behind them.

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Declaration of Competing Interest

The authors have no conflicts of interest relevant to this article to disclose.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jcrimjus.2021.101813.

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