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#### Types of crime and types of mechanisms:

#### What are the consequences for neighborhoods over time?

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### Biography

**John R. Hipp** is a Professor in the departments of Criminology, Law and Society, and Sociology, at the University of California Irvine. His research interests focus on how neighborhoods change over time, how that change both affects and is affected by neighborhood crime, and the role networks and institutions play in that change. He has published substantive work in such journals as *American Sociological Review, Criminology, Social Forces, Social Problems, Mobilization, City & Community, Urban Studies* and *Journal of Urban Affairs.* He has published methodological work in such journals as *Sociological Methodology, Psychological Methods*, and *Structural Equation Modeling.* 

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#### Abstract

Using a longitudinal dataset of 317 neighborhoods from 1996 to 2002 in Utrecht, The Netherlands, this study tests whether types of crime differentially impact a) the mechanisms of social disorganization theory, and b) residents' mobility behavior and attitudes towards the neighborhood. Neighborhoods with more cohesion have less violence two years later. Also, neighborhoods perceiving more violence experience lower levels of cohesion two years later. Higher levels of perceived violence were most important for explaining *who* moves out of the neighborhood, as such neighborhoods had more nonwhites and more lower income households at the next time point. Burglaries (a crime that occurs in private space) appear to increase residents' sense of feeling responsibility for the neighborhood.

Keywords: neighborhoods; crime; social disorganization theory

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#### Introduction

A challenge for scholars is exploring the dynamic nature of neighborhoods and the consequences of this dynamism for levels of crime. For example, social disorganization theory (Shaw and McKay 1942) posits that certain structural characteristics will affect the ability of residents to provide social control over time that would minimize crime. Studies in this literature have explored the relationship between neighborhood structural characteristics and such outcomes as violence (Bursik and Grasmick 1992; Sampson and Groves 1989; McNulty and Bellair 2003) property crime (Warner and Rountree 1997), school disorder (Welsh, Greene, and Jenkins 1999), and even general recidivism (Rose and Clear 1998). At the same time, a growing body of scholarship has explored possible feedback effects in which crime can bring about changes in neighborhoods through increased residential mobility or reduced social interaction between neighbors, leading to diminished social cohesion (Skogan 1990: 13; Steenbeek and Hipp 2011). An important question that is relatively under-addressed in these literatures is whether the mechanisms operating between both the causes, and the consequences, of neighborhood crime may work differently for *different types of crime*.

Criminologists are well aware that different crime types may have unique etiologies (Felson 2002). Nonetheless, most of the communities and crime literature has not explicitly considered that the two key mechanisms of cohesion and informal social control may be more effective in reducing some types of crime compared to others. For example, neighborhood cohesion is likely a more important mechanism for reducing types of crime that require a more concerted response on the part of residents to combat them. However, for crime types that can be addressed through individual behavior, direct social control behavior is likely be more effective. Furthermore, studies rarely make a distinction between whether these mechanisms reduce actual levels of crime, or residents' *perceptions* about the level of crime. Even if cohesion and informal social control behavior do not affect the actual level of crime in neighborhoods, they might still affect residents' *perceptions* about the level of crime, which may have

important consequences for future behavior of residents. Nonetheless, research has not systematically explored whether the mechanisms of social disorganization theory have different consequences for various types of crime.

Similarly, the growing literature exploring how crime might impact residents' attitudes and behavior (i.e., residential mobility, social cohesion, and collective efficacy) has typically not systematically tested whether certain types of crime have stronger effects on residents' attitudes and behavior than others. Given that some scholars argue that violent crime has particularly strong psychological effects on individuals (Zimring 1997; Hipp 2013), it may be more likely to impact residents' attitudinal change over time than other types of crime. Or, crime types that occur relatively frequently might strongly impact residents' sense of collective efficacy or cohesion. Furthermore, residents' *perceptions* of types of crime (as opposed to objective measures of crime) may be particularly likely to impact attitudes and activity on behalf of the neighborhood, suggesting that measuring such perceptions might in fact be quite important (Sampson and Raudenbush 2004; Hipp 2010b). In summary, understanding whether various types of crime, or residents' perceptions of crime, might have differential effects on residents' attitudes and behavior is of crucial importance for understanding neighborhood dynamics.

In this study, we explore to what extent the mechanisms operating between the causes and consequences of (perceived) neighborhood crime work differently for crime types along three dimensions. Using a neighborhood-level longitudinal dataset of the city of Utrecht, Netherlands, from 1996 to 2002, we construct measures of victimizations by three types of crime (namely, violent crime, burglary, and petty crime) and residents' perceptions of these three types of crime. These data allow us to test the relationship between crime and 1) cohesion, 2) residents' own expressed feelings of responsibility for the neighborhood, and 3) residents' actual informal social control *behavior* (Steenbeek and Hipp 2011).

#### **Theoretical model**

#### Forward stream part of the model

The social disorganization model of the Chicago School is a mainstay of the neighborhoods and crime literature, and it posits that neighborhoods with certain deleterious structural characteristicseconomic disadvantage, residential instability, and ethnic heterogeneity-will suffer from general social disorder and hence higher rates of crime (Shaw and McKav 1942; Bursik 1988). These scholars suggested that in neighborhoods with the key mechanisms of denser social networks and more voluntary associations residents will have a stronger sense of cohesion (Sampson 1991; Connerly and Marans 1985; Hunter 1975; Lee, Campbell, and Miller 1991) and therefore be more likely to provide the ultimate mechanism of informal social control to address crime (Warner 2007). Sampson and colleagues (Sampson, Raudenbush, and Earls 1997) suggested combining residents' shared expectations about informal social control along with social cohesion and mutual trust into a single measure of "collective efficacy", and posited that this would be most salient for fostering informal social control behavior on the part of residents. For all of these potential mechanisms, informal social control behavior arguably operates as the final mechanism in the causal chain leading to reduced crime (Steenbeek and Hipp 2011). That is, neighborhood structural characteristics may lead to more neighboring, general cohesion, or a sense of neighbors' willingness to engage in informal social control, but then these mechanisms would increase a resident's own likelihood of engaging in informal social control behavior, and this behavior would then reduce crime. Nonetheless, very little empirical evidence exists regarding the determinants of such behavior. The social disorganization model is displayed in part of Figure 1.

#### <<<Figure 1 about here>>>

In addition to this forward stream part of the model, scholars have emphasized possible feedback effects in which crime impacts residents' perceptions of cohesion and informal social control, as well as the structural characteristics of a neighborhood by inducing residential mobility (Skogan 1990: 10, 13). These effects are also captured in Figure 1. Crime is undesirable and should therefore have feedback effects on neighborhood structural characteristics through residential mobility. For example, residential mobility increases after experiencing a property crime event (Dugan 1999; Xie and McDowall 2008). And neighborhoods with more property or violent crime experience higher vacancy rates (Taylor 1995), population losses (Morenoff and Sampson 1997) residential instability (Boggess and Hipp 2010; Hipp,

Tita, and Greenbaum 2009), or both instability and vacancies (Hipp 2010a). And crime can also lead to a change in the racial composition due to the evidence of differential mobility in response to crime, especially violent crime, by minorities (Xie and McDowall 2010; Hipp 2011; Morenoff and Sampson 1997; Bursik 1986; Hipp 2010a, 2010c). For households that do not leave the neighborhood, increasing crime rates can affect their attitudes about the neighborhood: residents might perceive less cohesion and willingness to engage in activities to improve the neighborhood (Skogan 1990; Steenbeek and Hipp 2011). Despite these considerations, the extent to which *different types* of crime might impact the structural characteristics of neighborhoods through disproportionate residential mobility in response to crime is relatively understudied in this burgeoning literature. Likewise, few studies have systematically explored whether certain crime types more strongly impact residents' sense of cohesion and feelings of responsibility for the neighborhood.

#### Dimensions of crime

To explore the mechanisms of social disorganization theory and the feedback effects on residents' behavior and attitudes, we consider three key dimensions of crime: 1) the *violent/nonviolent* nature of the crime; 2) the *public/private* nature of the crime; and 3) the *frequency* of the crime. Although these dimensions are not mutually exclusive when considering specific crimes, we argue that these are nonetheless useful distinctions as they capture a wide range of phenomena and provide testable hypotheses based on these various dimensions. Ideally, we would have direct measures of these dimensions of crime events. We do not, but we suggest that these dimensions help in interpreting the results for the three crime types we measure: 1) violent crimes (which are violent and infrequent); 2) burglaries (which are nonviolent and private); and 3) petty thefts (which are nonviolent, typically public, and relatively frequent). Given the possible importance of residents' perceptions as opposed to actual crime rates, we also distinguish between perceptions and victimization. We derive general hypotheses for the mechanisms and the feedback effects for these different dimensions of crime.

Whether a criminal event is *violent* or not likely has consequences for social disorganization theory mechanisms. It is unlikely residents would directly intervene because of the seriousness of violent crime events (e.g., aggravated assaults, homicides, sexual assaults, robberies), and also because it is

unlikely that intervention could actually prevent a crime from occurring (Reynald 2010). This implies that direct informal social control behavior may not be able to reduce violent crime. Therefore, a more likely long-term response would be for the neighborhood to engage in an organized and concerted effort through either a neighborhood association petitioning the police, getting more "eyes on the street", or attempting to address more fundamental sources of the violence through social organizations. These considerations imply that attempting to reduce violent events in the long term requires a collective rather than an individual response, and thus neighborhood cohesion may be important for long-term reduction of violent crime. This implies our first hypothesis:

# H1: Neighborhoods with more cohesion at one time point will have lower levels of violent crime at the next time point

For the feedback part of the model, violent crimes likely have strong effects on residents' fear of crime given that they can cause physical harm (Zimring 1997). For example, the National Survey of Crime Severity (Wolfgang et al. 1985) found that respondents perceived violent crime events to be the most serious. There is evidence that violent crime in neighborhoods has a stronger effect on shaping residents' general perceptions of crime in the neighborhood than does property crime (Hipp 2013). Given that violent crime is unambiguously undesirable, it may be that although all want to leave such neighborhoods, only those with the greatest economic resources will be able to do so. Indeed, one study found that higher violent crime rates in neighborhoods led to increases in concentrated disadvantage ten years later (Hipp 2010a). And studies have found that home values fall in response to crime rates (Buck and Hakim 1989; Schwartz, Susin, and Voicu 2003; Thaler 1978), and some studies have found this effect is strongest for violent crime (Taylor 1995; Tita, Petras, and Greenbaum 2006; Hipp, Tita, and Greenbaum 2009). If residents perceive violent crime as evidence that the neighborhood lacks the ability or willingness to provide a collective response then it may also reduce perceptions of cohesion and willingness to engage in informal social control. For example, a study found that higher levels of violent crime (measured as robbery/assault) reduced surveillance (Bellair 2000). These considerations imply the following hypotheses:

H2: Neighborhoods with more violent crime at one time point will have more minority and lower income residents at the next time point

H3: Neighborhoods with more violent crime at one time point will have less cohesion and willingness to engage in informal social control at the next time point

The second dimension we consider is whether the criminal event occurs in *public or private* space. Crime events that occur in public locations are more likely to be perceived by residents as a collective problem and therefore in need of a collective solution. This suggests that a collective mechanism would be most useful for such crime types. In contrast, criminal events that occur in private space are less likely to foster a collective response, and a private response may be seen as more appropriate (Reynald 2011). For example, home burglaries by definition happen in private space, and arguably the most effective strategy for minimizing burglaries is personal action (i.e., installing an alarm, modifying the landscape to increase visibility, etc.). Although some collective behavior that can address burglaries might be employed—this includes informal social control action manifested as activities of neighborhood block groups and residents watching over one another's residences—this action arguably has a weaker effect on crimes that occur in private compared to those that occur in public. Thus, we hypothesize:

H4: Neighborhoods with more cohesion at one point in time will have fewer crimes in public space at the next time point

H5: Neighborhoods with more cohesion at one point in time will have no effect on crimes in private space at the next time point

Regarding the feedback part of the model, criminal events that occur in a private space may be perceived as a problem requiring individual behavior. For example, residents may perceive burglaries as less of a neighborhood problem given that they are a direct attack on one's home. In this case, residents may respond in an individualized fashion and engage in more individualized behavior. Residents may respond to burglaries by installing alarms or other devices to make it more difficult to access the unit. It is possible that residents may also to some extent perceive a criminal event that occurs in a private space as an indicator of a lack of cohesion or informal social control potential on the part of fellow residents

(given that public monitoring can impact criminal events in private locations to some extent). This could lead to reciprocating with a neighbor in watching over each other's home. For example, Bellair (2000) found that higher levels of burglary increased surveillance. However, we suggest that this is likely a smaller part of the total response to such crimes compared to those that occur in public spaces. On the other hand, crimes that occur in public (or on the outside of one's home)—both serious ones (e.g., aggravated assault and robbery) or minor ones (e.g., small thefts)—may be seen as a challenge to the social fabric of the neighborhood. If this is the case, crimes that occur in public would reduce levels of cohesion and willingness to engage in informal social control. Thus,

H6: Neighborhoods with more burglaries at one time point will be more active to improve the neighborhood at the next time point

H7: Neighborhoods with more public crime events at one time point will have lower cohesion and willingness to engage in informal social control at the next time point

A third important dimension of crime types is the *frequency* with which they occur. Typically, less serious crimes occur more frequently than more serious crimes, and even the safest neighborhoods can experience them: for example, in the U.S., even neighborhoods at the highest 5<sup>th</sup> percentile of safeness experienced 74 larcenies over a three year period in the National Neighborhood Crime Study (Peterson and Krivo 2010). Even if residents are willing to intervene when observing crimes that occur frequently, arguably the frequent occurrence of such crimes would highlight the need for a collective response rather than an individualized response. This suggests that for crimes that occur frequently, a collective response along with a sense of obligation to respond may be necessary for successfully addressing such crime. Cohesion among residents may be important for fostering such a collective response. Thus:

H8: Neighborhoods with more cohesion at one time point will have lower rates of frequent crime types at the next time point

It is likely that residents will be most aware of crime types that occur frequently. Such frequent crimes might be perceived as a chronic problem in the neighborhood requiring concerted action to improve the quality of life. Such frequently occurring minor crimes and disorderly events may suggest to

residents that the neighborhood lacks the ability of a collective response, which may therefore reduce residents' sense of cohesion in the neighborhood. Another consequence would be a sense that the neighborhood is out of control and therefore reduce a resident's sense of responsibility to provide informal social control.

H9: Neighborhoods with more minor crime incidents at one time point will have lower levels of cohesion and willingness to perform informal social control at the next time point

In addition to these three dimensions of crime, a distinction can be made between actual levels of crime and residents' *perceptions* of the level of crime. Perceptions of crime in part are based on the actual level of crime, but some perceptions are likely independent of the level of crime and these might be impacted by informal social control behavior and cohesion. Collective behavior geared towards addressing problems in the neighborhood might have an additional effect on residents' *perceptions* of the level of crime (beyond the amount it actually reduces crime). Thus, neighborhoods that are more cohesive may reduce the *perception* of crime, independent of the actual level of crime. This would not be a trivial achievement, as prior research suggests that fear and feeling unsafe, instigated by one's perception of crime, can impact residents' satisfaction with the neighborhood (Adams 1992; Sampson 1991), their sense of cohesion and willingness to engage in informal social control behavior (Skogan 1986), as well as their mobility decisions (Hipp 2010c; Xie and McDowall 2008).

H10: Neighborhoods with more cohesion at one time point will have lower levels of perceived crime at the next time point

It is also the case for the feedback part of the model that residents' *perceptions* of the level of crime—even if inaccurate—may impact subsequent behavior in different ways than objective measures of crime. These perceptions can be impacted by other characteristics, such as the racial composition of the neighborhood (Chiricos, Hogan, and Gertz 1997) or length of residence in the neighborhood (Hipp 2010b). There are consequences of these perceptions. Thus, research suggests that residents who perceive more crime in the neighborhood report a greater fear of crime (Skogan and Maxfield 1981), are less satisfied with the neighborhood (Hipp 2010d, 2009; Adams 1992) and report less attachment (Austin and Baba 1990). Given this evidence, it is likely that these perceptions of crime can also reduce

residents' sense of neighborhood cohesion, especially their perceptions of crime types that might require a collective response (i.e., violent crimes; frequent crimes). Thus:

H11: Neighborhoods perceiving more violent crime or frequent crime types will have lower cohesion at the next time point

#### Summary

In the present study, we consider whether the social disorganization theory mechanisms of cohesion and informal social control attitudes and behavior of residents impact different types of crime in a longitudinal setting. We also assess the effect of various types of crime on residents' attitudes toward the neighborhood, as well as their residential mobility behavior. We next provide a description of the data.

#### **Data and methods**

Data

The data used for this study come from the individual-level survey 'Nieuw Utrechts Peil' (NUP), provided by the Administrative Information Department, Administrative Affairs, City of Utrecht, The Netherlands. Utrecht is the fourth largest city in the Netherlands with a growing population of about 235,000 to 275,000 in the years of this study. Crime and public disorder in Utrecht is comparable to that of the three largest Dutch cities. Between 1996 and 2002, the years spanning our study, total crime in the Netherlands increased somewhat in the earlier years, but decreased slightly after 2002 (Bijl et al., 2009), with the exception of vandalism. The survey was conducted in 1996, 1998, 2000, and 2002 on a separate set of respondents at each wave. Therefore, it is not a longitudinal dataset, but rather a series of crosssections. A limitation of this is that it does not allow us to follow individuals over time, and therefore prevents us from looking at macro to micro linkages (Taylor 2011). Nonetheless, the fact that these are independent samples at each time point is advantageous for our questions posed at the neighborhood level regarding whether attitudes about cohesion and informal control indeed affect the amount of crime at the next time point (rather than simply capturing individuals' perceptions of such changes). The response rate was between 60 and 70 percent for all years.

We define "neighborhoods" as postal-5 codes, as they are small enough to be relatively homogeneous compared to larger aggregations.<sup>1</sup> These small units are about 0.05 square miles on average; in comparison, the median block group land area in Los Angeles, CA, is 0.1 square miles. Our variables are all measured at the postal code-5 level by combining the individual responses to the survey. There were a total of 22,670 respondents over the four waves of the survey. Of the 411 postal code-5's at least somewhat within residential areas, we included the 317 with an average of more than 10 respondents across the waves, and thus the postal-5 codes in our sample had a mean of 18 respondents and a standard deviation of 8.5 in each of the 317 postal code-5's measured at each of the years of the study. Of the postal code-5's we did not include, 33 almost entirely overlap with retail areas or parks, and the other 61 have substantial overlap with parks, railroad tracks, and commercial areas. The excluded postal codes are smaller than those in the analyses (.031 versus .016 square miles) and do not exhibit a clear spatial pattern. Although it would be preferable to have a census reporting on these neighborhoods, we have reason to believe that an average of 18 persons per unit is satisfactory given evidence of research using 8.5 residents on average to report on block groups that showed satisfactory reliability (Sampson and Raudenbush 2004), and another study that found 80% reliability for neighborhoods with 20 persons (Sampson, Raudenbush, and Earls 1997). Furthermore, we are only measuring central tendencies of neighborhoods (e.g., average values) rather than distributions (i.e., variance), which require larger samples.

We created six measures capturing the amount of crime in the neighborhood. The first three measures use individual reports of victimization for three types of crime: violent crime, burglaries, petty thefts. These questions ask "Can you for each of these incidents indicate whether you or someone from your household was victimized in the last 12 months, and if so, how often?" The response categories are: "no", "yes, in own neighborhood", "yes, somewhere else in Utrecht", "yes, somewhere outside of Utrecht". We coded it as a victimization event if they responded "yes, in own neighborhood". The *violent victimization* measure combines answers to two questions: 1) "threatened with physical violence", and "victim of physical violence". The *burglary victimization* measure combines answers to two

questions: 1) "has something been stolen from your home", and 2) "attempted burglary in home, without anything being stolen". The *petty theft victimization* measure combines answers to two questions: 1) something stolen from (the inside of) your car?; 2) "Something stolen or vandalized on the outside of your car (or one of your cars), for example a mirror, antenna, wheel or another part, disregarding any possible damage which was the result of a collision/accident?" For the three victimization measures, we computed counts of the number of crimes experienced in the neighborhood in the last 12 months and divided by the number of respondents in the neighborhood to compute rates.

The next three measures use individual reports on their *perception* of the amount of these three types of crime in the neighborhood. The perceptual questions ask the respondents "about unpleasant incidents, crimes and nuisances that can occur in your neighborhood. For each of these, can you indicate if these happen almost never, sometimes or often in your neighborhood?" One measure is a single question about home *burglaries* (break-in into homes). The measure of *violent crime* combines two questions asking about violent offenses (including assault, robbery, threats, rape) and bag robbery. The measure of *petty theft* combines three questions asking about 1) "bikes getting stolen"; 2) "theft out of (the inside of) cars"; 3) "damaging/destroying cars and theft from cars, for example hub caps". For the latter two measures, we computed the mean of the responses on this 0-2 scale.

Three measures captured hypothesized mediating effects. One measure is *neighborhood cohesion*, which is a scale combining the responses of each individual in the neighborhood to five questions measured on a five-point scale ("completely disagree, disagree, not agree/not disagree, agree, completely agree") assessing the amount of cohesion in the neighborhood. The original cohesion survey questions were (translated from the original Dutch): "people in this neighborhood hardly know each other", "people in this neighborhood get along nicely", "there is a lot of solidarity in this neighborhood", "I feel at home with the people living in this neighborhood", and "How attached are you to your neighborhood" (for this latter question the responses ranged from very unattached, unattached, neither, attached, very attached). The five items scaled very well together with an average Cronbach's alpha of .85 across all years and neighborhoods. We first estimated a principal components analysis (PCA) on the variables composing each of the indices, and computed standardized factor scores based on regression

scoring from this PCA. The other mediating variables capture the amount of informal social control in the neighborhood in two different fashions. The first approach captures residents' *feeling responsibility for the neighborhood*. This is based on a single question whether they "felt co-responsible for the livability and safety of the neighborhood", which reflects potential for neighborhood-level social control. This is aggregated to the neighborhood level by computing the proportion who said "yes" to this question across the respondents of the postal-5 code. The second approach captures the extent to which respondents have actually been *active to improve neighborhood*. Specifically, the single question asks whether they had "been active to improve the livability and safety of the neighborhood" in the last year. We calculated the proportion of residents in a postal-5 code reporting engaging in such behavior.<sup>2</sup>

We highlight that the measures of cohesion and perceived crime all ask respondents to report on characteristics of the neighborhood, whereas the measures of victimization, willingness to perform informal social control, and informal social control behavior ask about an individual's own behavior or personal attitudes. Therefore we adopted different approaches in constructing these two sets of measures. For the latter measures, we simply computed the proportion experiencing such an event or engaging in the activity. For the measures assessing the neighborhood, we adopt the common approach of correcting for individual-level biases with the 'ecometrics' method (Raudenbush and Sampson, 1999). This accounts for compositional effects in which neighborhood assessments may be systematically affected by the characteristics of respondents in the neighborhood. This entailed a two-step approach. We first estimated fixed effects models that included indicator variables for all postal-5 codes in the area, as well as several individual characteristics that might systematically bias perceptions.<sup>3</sup> In the second step, the estimated coefficients for each of the neighborhood from the first step analyses were used as unbiased estimates of the amount of the construct in the neighborhood (e.g., cohesion, perceived crime, etc) in the final models.<sup>4</sup> Thus, these measures capture the neighborhood mean for the individual-level measures described earlier.

We included three structural measures of the neighborhood that the social disorganization model posits will have important consequences for neighborhood crime. These are based on respondents to the survey. The first is economic resources, measured as the *average household income* reported by the residents of the postal-5 code (this was an ordinal variable with 6 categories in the first two waves and 7

categories in the last two waves, and thus is not comparable across waves). The second is ethnic homogeneity, which is measured as the *percent Dutch* in the postal-5 code (given that in this context the percentages of the other groups are not large enough to justify computing a more general measure of heterogeneity such as a Herfindahl index). The third measure is *residential instability*, which computes the proportion of residents who moved into their unit in the last two years.

The summary statistics for the variables included in our models are presented in Table 1. There were only modest levels of missing data for the individual level measures—although 16.8% were missing for the question about income, the rest of the variables typically had less than 5% missing values—nonetheless, we accounted for this missingness through multiple imputation. This requires the less stringent assumption of missing at random rather than assuming missing completely at random, which is required when performing listwise deletion; furthermore, the analyses gain statistical power by not losing cases due to missingness on individual measures.<sup>5</sup> The average correlations over the four waves among the crime measures and the neighborhood demographic measures are provided in Appendix Table A1, and show no large values.

#### <<<Table 1 about here>>>

#### Methods

We estimated two cross-lagged longitudinal models in a simultaneous equation modeling framework (one for victimization, one for perceptions). This approach allows us to take into account the possibility of autocorrelated error structures over time (which is accomplished by allowing the error terms of adjacent time periods for each outcome variable to correlate), and changing levels of crime over time (which is accomplished by estimating a unique intercept value at each timepoint). Note that in each model there are nine separate equations (each measure in Figure 1 that has arrows pointing towards it represents an equation in which the particular variable is the outcome measure, and there are three crime types included in the model). We simultaneously estimate an equation for each of the nine outcome variables, and the general form of these equations is:

(1) 
$$y_{1t} = \alpha_t + \beta y_{1t-1} + BY_{t-1} + \rho W y_{1t-1} + \varepsilon_{1t}$$

where  $y_{It}$  is the variable of interest being explained (say, the violent victimization rate) which is measured at time *t*,  $\alpha_t$  is an intercept at each time point,  $y_{It-I}$  is the violent victimization rate at the previous time point which has a  $\beta$  stasis effect,  $Y_{t-I}$  is a matrix of the other endogenous variables in the model measured at the previous time point, B is a vector that captures the effect of these other measures on the violent victimization rate,  $Wy_{It-I}$  is a vector of the spatially lagged outcome variable measured at the previous time point and  $\rho$  is the parameter that captures its effect on the violent victimization rate, and  $\varepsilon_I$  is an error term with an assumed normal distribution. Given that we have four waves (t=1-4)(1996, 1998, 2000, 2002), the equation for each outcome appears three times (as it cannot be included for the first wave as there are no t-1 observations at that point).

It is important to account for spatial effects given that they are likely prevalent when small units of analysis are used (Bernasco 2010; Weisburd, Bernasco, and Bruinsma 2009). Given the often strongly significant spatial lag effects we detect in our models, this is likely more characteristic of the true spatial process than a spatial error model. To account for spatial lag effects, we first created a spatial weights matrix in which each postal-5 code was linked to its five nearest neighbors as a contiguity matrix (we do not use a distance decay), and then computed spatially lagged measures by multiplying the values of the time lagged outcome variable in these neighborhoods by this weight matrix (row standardized). Note that we are capturing the five nearest units that are in our sample—and thus primarily residential—and therefore the "nearby" area does not include any non-residential units. Consistent with the rest of our model, we temporally lagged these spatially lagged measures, which mirrors an approach adopted by other studies (Hipp, Tita, and Greenbaum 2009; Bernasco and Block 2011; Steenbeek and Hipp 2011).

We estimated two separate models: one that included the three victimization measures, and one that included the three perceived crime measures. The model estimated each time is depicted in Figure 1, with the only change being that three different types of crime replace the single "crime" measure. Note that whereas this theoretical model posits that the effects of certain measures (i.e., the demographic variables, cohesion) will be entirely mediated by the paths shown, we nonetheless assess whether this is actually the case by including these additional direct paths in the equations to assess whether they are

indeed nonsignificant. We assessed the overall fit of the models, and determined that it was quite satisfactory. The root mean squared error of approximation (RMSEA) values are 0.47 and 0.06 for the two models. Given that scholars typically suggest that values below 0.06 to 0.08 are satisfactory (Hu and Bentler 1999), and given that multiple imputations increase the average model fit over each imputation, these results suggest a reasonable model fit.

#### Results

#### Crime victimization model

We begin by presenting the results of the model including the three crime victimization measures simultaneously. We first focus on the potential mediators of cohesion and informal social control. Column 1 in Table 2 shows the outcome of cohesion at the next time point. We see that neighborhoods with more cohesion at the previous time point report more cohesion at this time point (b=.498), exhibiting stability over time in the construct (recall that these are unique samples of residents at each time point). There is also evidence that postal-5 codes surrounded by areas with higher levels of cohesion at the previous time point their reported level of cohesion at the current time point (b=.29). Thus, the effects of the other measures in the model are net of these temporally lagged effects of cohesion. We generally see evidence consistent with the U.S. context, as locations with higher income (b=.069) and higher homogeneity (a higher percentage Dutch) (b=.313) have more cohesion at the next time point (though this is only significant at p < .10). There is no evidence of a feedback effect on cohesion from victimization for any of the three types of crime in this model.

#### <<<Table 2 about here>>>

In the column predicting feeling responsibility for the neighborhood (column 2), we see stasis over time for this measure (though not as strong as for cohesion), as both the temporally lagged measure and the spatially/temporally lagged measure have significant positive effects. Nonetheless, even controlling for the prior level of feeling responsibility, locations with higher levels of cohesion at the previous time point have higher levels of feeling responsibility at the current time point. This is consistent with the hypothesis that cohesion does indeed foster greater willingness to provide informal

social control. We see that the effect of instability on levels of feeling responsibility is largely mediated by cohesion (it does not have a direct significant effect in column 2). However, neighborhoods with higher average income at one point in time report feeling more responsibility at the next time point, which is above and beyond their indirect effect through increased cohesion. Neighborhoods with fewer Dutch report feeling more responsibility at the next time point. We do see an interesting feedback effect as burglary victimizations actually have a *positive* effect on feeling responsibility for the neighborhood, suggesting that they may actually galvanize residents into action.

Column 3 asks whether this cohesion and willingness to provide informal social control actually translate into more informal social control behavior (controlling for the level of crime). We see stasis effects, as neighborhoods with more persons active in the neighborhood at one time point also have more persons active the following time point (b=.078). Controlling for previous levels of actual behavior, although feeling responsibility does not impact actual behavior, reported cohesion actually has a modest positive effect on actual behavior (p < .10). Neighborhoods with more residential instability at the previous time point report somewhat less informal social control activity in the neighborhood. We see that burglary victimization is again galvanizing as it has a modest positive effect on activity to improve the neighborhood (p < .10).

In this same model, the three crime victimization types are included as outcome variables (columns 4-6). There is a strong stasis effect as the level of crime in the neighborhood at the previous time point has a significant positive effect on the amount of crime at the current time point (except violent crime victimization), and the level of crime in surrounding neighborhoods at the previous time point always has a strong positive effect on the crime rate at the current time point. Thus, the effects of our other covariates in these equations are controlling for these strong stasis effects of neighborhood levels of crime.

Turning to the question of whether more activity to improve the neighborhood leads to less crime at the next time point, we see no evidence for this hypothesis as this effect is not significantly negative for any of these crime types. In fact, we actually see evidence that neighborhoods more active to improve the

neighborhood at the previous time point report *higher* levels of burglary victimization (column 5) at the current time point (b=.144).

We do not find that *feeling responsibility* for the neighborhood reduces the level of crime at the next time point for these three measures of crime victimization. Furthermore, the same non-result was detected in an ancillary model that did not include the measure of activity to improve the neighborhood (to assess whether the behavioral measure was simply "soaking up" this effect). On the other hand, neighborhoods reporting more cohesion at one time point report a lower violent crime victimization (b=-.014) at the next time point (column 4).

There is modest evidence that the neighborhood structural measures have a direct effect on these crime types. Neighborhoods with higher average income have higher levels of petty theft victimizations at the next time point, but this likely captures an opportunity effect. And neighborhoods with more instability have higher burglary and petty theft victimizations. Although the effects for percent Dutch and average household income are insignificant, their impact on violence works through their effect on cohesion. For example, a neighborhood with more Dutch or higher income will have more cohesion at the next time point (column 1) and that higher cohesion will reduce violent victimizations at the subsequent time point (column 4) (these indirect effects all significant at p < .05).

Columns 7, 8, and 9 capture the feedback effect of these crime victimizations on neighborhood demographic change. In column 7 we see that neighborhoods with higher burglary victimization rates at one time point have higher levels of residential instability at the next time point (b=.078), whereas the other two crime types are not significant in this model. On the other hand, we find that it is only *violent* victimizations that change the composition of the neighborhood, as higher levels of violence result in fewer percent Dutch at the next time point.

#### Crime perceptions model

We next turn to the results of the model including the three measures of *perceptions* of crime in Table 3. Many of the results in this model are similar to those for the crime victimization model, so we focus on the results for the crime perception measures as covariates, or as outcomes. In the column predicting cohesion (column 1), neighborhoods with higher levels of perceived violence report lower

levels of cohesion at the next time point (b=-.079). Likewise, in column 2 perceived violence (b=-.056) is more important for reducing levels of feeling responsibility for the neighborhood compared to perceptions about burglary or petty theft. Recall that none of the victimization measures showed a negative effect with these attitudes, suggesting that it is only these *perceptions* of violence that are important for impacting cohesion or feeling responsibility for the neighborhood. It is worth noting that we also estimated ancillary models which included only one crime type at a time (rather than three simultaneously as we do here), and in those models it appeared that neighborhoods with higher perception of petty theft had lower cohesion and feeling responsibility for the neighborhood at the next time point; these full models, however, demonstrate that it is the perception of violent crime that is more important for bringing about these attitudes compared to perceptions of more minor crimes. There is, however, no evidence that perceptions of any of these crime types impact residents' actual behavior to improve the neighborhood at the next time point (column 3).

#### <<<Table 3 about here>>>

Turning to columns 4-6 in which the perceptions of three types of crime are the outcomes, we see that more cohesive neighborhoods have lower perceptions of violent crime at the next time point (b=-.091). This parallels the finding in the violent *victimization* model, suggesting the cohesion is particularly important for reducing violence in neighborhoods (in support of hypothesis 1). We see in column 5 that neighborhoods that are more active to improve things actually have higher levels of perceived burglary at the next time point (b=.17), which parallels the results for burglary victimization. Thus, there is little evidence that such activity can reduce a private crime such as burglary. It is notable that whereas more residential instability was associated with higher burglary and petty theft victimization at the next time point in the victimization model (and higher average income was associated with more petty theft at the next time point), there is no evidence of such a relationship for the *perceptions* of residents regarding these crime types.

Finally, in columns 7-9 we see the feedback effects of these perceptions of crime on the neighborhood demographic characteristics. Whereas we saw in the victimization model that only burglary victimization increased residential mobility, here it is the perception of petty theft that is

important for increasing residential instability at the next time point (b=.069 in column 7).<sup>6</sup> However, we see that it is the perception of violence that has the strongest effect on changing *who* moves out of neighborhoods. Higher levels of perceived violence in a neighborhood are associated with fewer percent Dutch and lower average income at the next time point. When estimating ancillary models with only one crime type at a time, it appeared that higher levels of perceived burglary were associated with fewer percent Dutch at the next time point; we see in column 8 that this relationship was reduced to nonsignificance when accounting for the level of perceived violence, suggesting that violence perceptions are more important for such selective mobility.

#### Sensitivity analyses

Given that two of our measures arguably have relatively low reliability—just one yes/no variable captures the attitude towards feeling responsibility for the neighborhood and just one ves/no question captures being active in the neighborhood—we assessed the robustness of the model results when accounting for the lower reliability of these two measures. To accomplish this in a structural equation modeling framework, each of these measures is reformulated as a latent variable with a single indicator with the variance of the error term set to a value to represent a particular reliability level. For a discussion of this technique, see Bollen (1989). (For examples of this approach in applied research, see Paxton 2002; Lakon, Hipp, and Timberlake 2010). Although choosing particular reliability values is of necessity somewhat arbitrary, we chose values that are somewhat common in the literature and therefore assessed how the results change when re-estimating the models with the reliability for each measure set to values of .7, and values of .5. There were only a few modest differences for these two variables in these ancillary models (results available upon request). The effect of cohesion on feeling responsibility for the neighborhood is weaker but still significant when reliability is set to .7, but nonsignificant with reliability set to .5. We do find that feeling more responsible in the neighborhood modestly increases activity to improve the neighborhood at the next time point, and this activity now has an even stronger positive effect on burglary (both victimizations and perceptions) at the next time point. And the positive effect of burglary victimizations on activity to improve the neighborhood at the next time point was stronger.

Thus, although these two measures show somewhat stronger results when accounting for their lower reliability, the general pattern of the results remain relatively unchanged.

Another issue that some have suggested is that neighborhood processes differ based on where neighborhoods are in the life cycle (Schuerman and Kobrin 1986; Walker 2007). Although testing such a hypothesis requires a large number of neighborhoods for statistical power, we performed an approximate test by splitting our sample into high and low crime neighborhoods (based on the mean level of crime) and estimating separate models. Thus, we are comparing neighborhoods approximately early in their life cycle (low crime neighborhoods) and those approximately later in their life cycle (high crime neighborhoods). Although most of the results were similar across neighborhood career, there were a few differences. In the forward stream of the model, the only difference was that in low crime neighborhoods higher income is associated with lower violence at the next time point (but not in high crime neighborhoods). None of the mechanisms differed over the split samples. There are more differences in the feedback part of the model. For low crime neighborhoods, higher levels of violence (victimizations or perceived) and higher levels of perceived burglary strongly reduce the number of Dutch in the neighborhood (but there is no such effect for high crime neighborhoods). Higher perceived petty theft results in more residential instability at the next time point for low crime neighborhoods but this effect is weaker for high crime neighborhoods. Whereas more perceived violence reduces feelings of responsibility to improve the neighborhood, this effect is much stronger in low crime neighborhoods. On the other hand, only in high crime neighborhoods was the positive effect of burglary victimization on feelings of responsibility to improve the neighborhood present, as well as a positive relationship between neighborhoods feeling more responsibility and activity to improve the neighborhood.

#### Conclusion

This study has extended social disorganization theory by systematically testing whether the mechanisms of this model behave differently for different types of crime. Specifically, we tested whether victimizations of three types of crime, or perceptions of three types of crime, are differentially affected by social control and cohesion. We also tested whether residents' cohesion and willingness to engage in social control, as well as their actual social control behavior, are differentially impacted by these various

types of crime and perceptions of these crime types. Our findings therefore extend the literature by showing that whereas crime appears to have important implications for how neighborhoods change over time, *how crime affects neighborhoods differs depending on the type of crime that is experienced in the neighborhood.* We next discuss the results of our 11 hypotheses, which are summarized in Table 4.

#### <<<Table 4 about here>>>

First, we extended the prior literature by testing and finding that cohesion has a strong effect on *certain* types of crime, although, just as importantly, we found that it did not matter for some types of crime. Thus, neighborhoods with more cohesion at one time point had a greater sense of feeling responsibility at the next time point. Nonetheless, even when controlling for these informal social control attitudes and behavior, the level of cohesion in the neighborhood still had an independent negative effect: highly cohesive neighborhoods have lower levels of violent crime, measured either as perceptions or as victimizations. These results were consistent with our hypotheses 1 and 10. We also found no relationship between cohesion and the private crime of burglary, consistent with hypothesis 5. But whereas cohesive neighborhoods were not associated with lower burglary rates, they were associated with somewhat lower *perceptions* of burglary at the next time point, which is also consistent with hypothesis 10. However, the hypotheses that cohesion would reduce minor crimes or public crimes were not supported, as there was no reduction in petty thefts.

Second, we extended the existing literature on how crime impacts residents' attitudes as well as their residential mobility behavior by showing that such effects differ based on the *type of crime* under study. We found that these differences occurred for crime types along three dimensions. For example, the *frequency* of crime events was most important for explaining general mobility. Neighborhoods with more burglary victimizations experienced higher overall residential mobility at the next time point. This may reflect the fact that burglary victimizations are a traumatic effect that can induce mobility behavior (Dugan 1999; Xie and McDowall 2008). Notably, general perceptions of burglary rates had no such effect. Neighborhoods in which residents perceived more petty theft experienced higher overall residential mobility at the next time point, and this pattern was even stronger in low crime neighborhoods. Although we had hypothesized that such minor, frequent crimes would reduce cohesion or feeling

responsibility for the neighborhood, no such effect was detected and instead the perception of them is more important for increasing general out-mobility. However, these minor types of crime did not disproportionately affect *who* moves out of or into neighborhoods.

For understanding who moves out or moves in, it appears that the *violence* of crimes has the strongest impact. Neighborhoods with more violent victimizations experience an increase in ethnic minorities at the next time point, and this effect was strongest in low crime neighborhoods. And neighborhoods in which residents *perceive* more violence have more minorities and lower income residents at the next time point. This important role of violence for who moves in or out mirrors research in a U.S. setting at the household level finding that racial/ethnic minorities and lower income residents are less likely to leave neighborhoods with more violence (Hipp 2010c, 2011). And it also mirrors U.S. neighborhood-level research finding that violence disproportionately results in out-mobility of non-whites and higher income residents (Morenoff and Sampson 1997; Hipp 2010a). An important contribution of the present study was simultaneously considering other crime types and nonetheless finding that violence has the strongest impact.

It also appeared that the perception of the level of violent crime had the strongest impact on residents' attitudes. As we hypothesized, neighborhoods with higher levels of perceived violence at one time point had lower levels of cohesion and feelings of responsibility for the neighborhood at the next time point. Few studies have tested this hypothesis in a longitudinal setting. The evidence that residents' perceptions of neighborhood crime are most highly related to violent crime (Hipp 2013), and that perceptions of crime are negatively related to neighborhood satisfaction (Hipp 2010d, 2009; Adams 1992) and attachment (Austin and Baba 1990) suggests that this study's finding regarding perceptions of violence extends the notion that violence—more than other types of crime—has a particularly strong impact on residents' attitudes (Zimring 1997).

The *public/private* nature of crime only had modest effects. Although we hypothesized that more public crimes would result in lower cohesion and feeling responsibility for the neighborhood, this was not the case. Whereas perceptions of violent crime and petty theft (our two measures of crimes that typically occur in public) were indeed negatively related to these attitudes at the next time point in separate models,

the effect for petty theft was reduced to effectively zero when accounting for the perceived level of violence in the neighborhood. Thus it appears that the dimension of violence, and not the public/private nature of the location of the crime, is what is important for impacting residents' attitudes. We did find that burglary victimizations—a crime that generally occurs in private space—did foster *greater* feelings of responsibility (especially in high crime neighborhoods) and modestly more activity to improve the neighborhood. This was consistent with our hypothesis that crimes that take place in private space may bring about a sense of a need for individual action, and less of a sense of an attack on the cohesion of the neighborhood.

It is interesting to note that we found no evidence that actual behavior to improve the neighborhood reduced any type of crime at a later time point. Given the paucity of studies assessing whether such behavior indeed impacts levels of crime over time, our non-findings suggest that it is still an open question whether such behavior can indeed impact crime levels. Nonetheless, we acknowledge that this was a somewhat limited binary measure of behavior by residents in a neighborhood. We attempted to assess the impact on the analyses of the limited reliability of this measure (and the measure of feeling responsibility for the neighborhood) my taking into account the lower reliability of these measures. There was still no evidence in these ancillary models that such behavior reduces crime rates at the next time point, contrary to the hypothesis of social disorganization theory. Nonetheless, the findings should be interpreted with this measurement limitation in mind, and highlights the importance of measurement (Taylor 2002).

We acknowledge some limitations of this study. Although our study focused at the neighborhood level and provided key insights, we were unable to test these processes over time at the individual level given that our data were a series of cross-sections. Future research will want to explore what actually brings about behavior on the part of individuals within a longitudinal framework (Taylor 2011). Given that respondents are asked to report on the number of victimization events that occurred over a previous period of time, there is the risk of telescoping of responses as residents may include events that occurred further back in time. This is a well-known problem, although it is unclear how it might systematically bias our results. Another limitation is that our victimization measures only reported that the event

occurred somewhere in the neighborhood, and did not indicate whether it occurred in public or private locations. We instead assumed this based on the type of crime, and where such crimes typically occur. Nonetheless, our findings here focusing on where crimes typically occur are suggestive, and highlight that future studies will want to directly measure this. We were also limited to the specific types of crime based on what was asked in the survey, thus we cannot generalize to other types of crime. We were limited to just four time points over 8 years, which limits our ability to generalize to longer-trend patterns. Although determining short-term changes is important, future research will want to focus on possible long-term consequences in neighborhoods. It is difficult to tease out the effects of different types of crime simultaneously in the same model, although we have attempted it here. This may be more feasible in future studies using data over longer periods of time to allow observing such differences. We also lacked the ability to fully test whether these processes differ depending on the neighborhood's stage in the life cycle, although the approximation splitting the sample into high and low crime neighborhoods provided some intriguing results. We note that the self-reported victimization data allowed us to assign crime events to the neighborhood, but not to specific locations within the neighborhood (e.g., whether in public or private locations). Although the location of occurrence is unambiguous for the burglary (i.e. a private home) and minor theft (i.e. the public space) measures, some of the violent crime events may have occurred in a private home (in the neighborhood).

In conclusion, we have shown that it is important to distinguish between different types of crime when exploring the dynamics of neighborhoods. There is reason to expect that even if cohesion among residents is effective for reducing some types of crime, it may not be effective in reducing all types of crime. Likewise, there are key differences in how some types of crime affect residents' attitudes and behaviors. We distinguished crime along three dimensions: 1) the *violent/nonviolent* nature of the crime; 2) the *public/private* nature of the crime; 3) the *frequency* of the crime. We also distinguished between crime victimizations and perceptions. It appears that residents perceiving more violent crime has a strong negative effect on residents' sense of cohesion and feelings of responsibility to the neighborhood at the next time point. Given that this cohesion appeared to reduce violence at the next time point, this is clearly a potential vicious cycle worth understanding better.

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- York: Oxford.

## Endnotes

<sup>1</sup> The zip code system in the Netherlands consists of four numbers and two letters for every address: the first two numbers indicate region, the third and fourth number district within municipality, and the letters refer to neighborhood and street respectively. Each six-position zip code has 20 addresses on average. We chose to define a neighborhood as the addresses within a zip code area of four numbers plus one letter (e.g. 3512J). Such an area includes 230 addresses on average in the Netherlands and corresponds to the walk of a postman. This strategy has been used before by Dutch researchers (Volker, Flap, and Lindenberg 2007).

<sup>2</sup> These factor analyses were conducted on all waves at once by stacking the data long. This allowed us to estimate factor loadings constrained to be equal over all waves. As a consequence, the factor scores are standardized over the entire period of the study, rather than being standardized within each year (which would preclude studying how the level of these constructs change over time).

<sup>3</sup> The following individual level characteristics were included in the model: female, age, age squared, length of residence in the neighborhood (three indicator variables of less than 2 years, 2 to 5 years, and 5 to 10 years, with the reference category being more than 10 years), household income (eleven categories specified as indicator variables for maximal flexibility in the relationship), education level (with six categories specified as indicator variables), homeowner, employed, ethnic group (indicators for Moroccan, Turkish, and Other race, with Dutch as the reference category), and marital status (indicators for single parent household, married with no children, married with children, and single as the reference category).

<sup>4</sup> Another approach to computing these estimates would use a Bayesian approach and output empirical Bayes estimates for each neighborhood. However, both approaches yield very similar estimates and therefore the choice does not impact the results: a previous study employing this same dataset found very high similarities whether constructing empirical Bayes estimates or the unbiased estimates we use here (see Steenbeek and Hipp 2011, footnote 12 on page 846). <sup>5</sup> The data were imputed using an MCMC procedure implemented in Stata 9. We included all of the

<sup>5</sup> The data were imputed using an MCMC procedure implemented in Stata 9. We included all of the individual-level measures used in the analyses in the imputation procedure, including the individual-level characteristics that we included as possible biasing effects when constructing our neighborhood-level measures, the variables comprising the cohesion and perceived crime scales, and our measures of shared feelings of responsibility, and actual social control behavior. Given the rate of missingness in our data, we imputed the dataset five times.

<sup>6</sup> When we estimated a model with just perceptions of violence as the only crime measure, the relationship between perceived violence and residential stability was essentially zero. Thus, the modest negative effect detected in column 7 of Table 3 only occurs when controlling for the level of perceived petty crime. These two measures are correlated .48, and thus tend to co-occur to some extent.

## **Tables and Figures**

Table 1. Summary statistics of variables used in	analyse	S						
	199	96	199	98	20	00	200	)2
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Violent crime victimizations (rate)	0.047	0.070	0.057	0.115	0.064	0.082	0.074	0.112
Burglary victimizations (rate)	0.190	0.186	0.150	0.224	0.120	0.126	0.146	0.158
Petty theft victimizations (rate)	0.309	0.212	0.307	0.290	0.320	0.199	0.383	0.260
Perception of violent crime	0.272	0.431	0.324	0.609	0.303	0.421	0.808	0.464
Perception of burglaries	0.941	0.318	0.615	0.401	0.730	0.300	0.515	0.304
Perception of petty theft	0.762	0.328	0.715	0.402	0.916	0.322	1.005	0.321
Proportion Dutch	0.797	0.174	0.684	0.345	0.833	0.142	0.858	0.137
Average household income	3.766	0.867	3.792	0.955	4.255	0.821	4.261	0.883
Residential instability (proportion new residents)	0.176	0.137	0.167	0.193	0.171	0.135	0.165	0.136
Cohesion (factor score)	-0.401	0.521	-0.265	0.615	-0.213	0.508	-0.299	0.479
Feel responsibility for neighborhood (proportion)	0.849	0.116	0.824	0.208	0.880	0.109	0.876	0.113
Active to improve neighborhood (proportion)	0.210	0.136	0.207	0.184	0.261	0.159	0.316	0.169

N = 317 postal 5 codes. Average household income is measured on an ordinal scale and cannot be compared across waves given that it is measured in guilders at the first three waves and in euros in the last wave. Cohesion and the perceptions of crime are factor scores that only have relative meaning across waves.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Cohesion	Feel responsibility for neighborhood	Active to improve neighborhood	Violent crime victimization	Burglary victimization	Petty theft victimization	Residential instability	Percent Dutch	Average household income
Active to improve neighborhood (t-1)			0.078 *	-0.006	0.144 **	0.022			
			(2.41)	-(0.28)	(4.98)	(0.46)			
Feel responsibility for neighborhood (t-1)		0.082 **	0.060	0.005	-0.009	-0.050			
		(2.65)	(1.41)	(0.19)	-(0.25)	-(0.78)			
Cohesion (t-1)	0.498 **	0.039 **	0.019 †	-0.014 *	0.002	0.012			
	(18.64)	(4.86)	(1.81)	-(2.27)	(0.25)	(0.82)			
Percent Dutch (t-1)	0.313 **	-0.068 *	-0.018	-0.013	-0.009	-0.082 †		0.202 **	
	(3.60)	-(2.44)	-(0.54)	-(0.62)	-(0.32)	-(1.73)		(7.53)	
Average household income (t-1)	0.069 **	0.030 **	0.000	0.001	0.002	0.027 **			0.453 **
	(4.12)	(5.48)	(0.05)	(0.23)	(0.31)	(2.85)			(12.21)
Residential instability (t-1)	-0.163 †	0.001	-0.064 †	0.013	0.086 **	0.106 *	0.184 **		
	-(1.81)	(0.04)	-(1.90)	(0.53)	(2.72)	(2.22)	(5.63)		
Violent crime victimization (t-1)	-0.057	-0.024	0.011	0.042			-0.013	-0.103 *	0.268
	-(0.43)	-(0.58)	(0.20)	(1.23)			-(0.24)	-(2.14)	(0.96)
Burglary victimization (t-1)	0.028	0.053 *	0.056 †		0.190 **		0.078 *	-0.027	0.114
	(0.36)	(2.12)	(1.75)		(6.48)		(2.42)	-(0.94)	(0.70)
Petty theft victimization (t-1)	0.028	-0.026	-0.028			0.081 *	0.028	-0.003	-0.075
	(0.52)	-(1.49)	-(1.17)			(2.38)	(1.30)	-(0.13)	-(0.64)
Spatially lagged outcome variable (t-1)	0.290 **	0.132 *	0.046	0.307 **	0.118 **	0.296 **	0.266 **	0.252 **	0.308 **
	(8.87)	(2.54)	(0.78)	(5.49)	(2.74)	(5.53)	(5.04)	(6.79)	(7.34)

\*\* p < .01 (two-tail test), \* p < .05 (two-tail test), † p < .10 (two-tail test). T-values in parentheses. Results from full model estimated with maximum likelihood estimator. N = 317 postal units

	(1)		(2)		(3)		(4)		(5)	(6)		(7)		(8)	(9)
	Cohesi	on	Feel responsibi for neighborhc	lity ood	Active to improve neighborho	c e bod	Percept of viole crime	ion nt	Perception of burglary	Percept of pet theft	tion ty	Resident instabili	ial ty	Percent Dutch	Average household income
Active to improve neighborhood (t-1)					0.075	*	-0.069		0.170 *	0.015					
					(2.29)		-(0.81)		(2.54)	(0.25)					
Feel responsibility for neighborhood (t-1)			0.059	Ť	0.066		-0.034		0.019	-0.015					
			(1.90)		(1.53)		-(0.29)		(0.23)	-(0.20)					
Cohesion (t-1)	0.473	**	0.024	**	0.020	÷	-0.091	**	-0.039 †	-0.008					
	(17.22)		(2.86)		(1.76)		-(3.07)		-(1.88)	-(0.44)					
Percent Dutch (t-1)	0.305	**	-0.076	**	-0.014		-0.032		-0.084	0.047				0.201 **	
	(3.50)		-(2.73)		-(0.44)		-(0.36)		-(1.30)	(0.87)				(7.48)	
Average household income (t-1)	0.065	**	0.029	**	-0.002		-0.006		0.025	0.007					0.436 **
	(4.09)		(5.66)		-(0.37)		-(0.40)		(1.64)	(0.58)					(12.17)
Residential instability (t-1)	-0.153	Ť	0.000		-0.065	†	-0.001		0.046	0.052		0.167	**		
	-(1.67)		(0.01)		-(1.78)		-(0.01)		(0.68)	(0.88)		(5.05)			
Perception of violent crime (t-1)	-0.079	*	-0.056	**	-0.015		0.239	**				-0.019	†	-0.023 *	-0.159 *
	-(2.41)		-(5.90)		-(1.17)		(5.97)					-(1.75)		-(1.99)	-(2.49)
Perception of burglary (t-1)	0.045		0.012		0.027				0.278 **			-0.007		-0.016	0.133
	(0.99)		(0.92)		(1.50)				(9.05)			-(0.47)		-(1.09)	(1.52)
Perception of petty theft (t-1)	-0.032		0.008		0.014					0.397	**	0.069	**	0.008	0.054
	-(0.79)		(0.58)		(0.81)					(11.86)		(4.01)		(0.58)	(0.62)
Spatially lagged outcome variable (t-1)	0.277	**	0.086	†	0.043		0.496	**	0.231 **	0.403	**	0.228	**	0.216 **	0.293 **
	(8.33)		(1.65)		(0.73)		(10.25)		(4.75)	(9.29)		(3.93)		(5.52)	(6.86)

\*\* p < .01 (two-tail test), \* p < .05 (two-tail test), † p < .10 (two-tail test). T-values in parentheses. Results from full model estimated with maximum likelihood estimator. N = 317 postal units

Tab	le 4. Results for hypotheses	
	Hypothesis	Support?
1	Neighborhoods with more cohesion at one time point will have lower levels of violent crime at the next time point	Yes
2	Neighborhoods with more violent crime at one time point will have more minority and lower income residents at the next time point	Yes
3	Neighborhoods with more violent crime at one time point will have less cohesion and willingness to engage in informal social control at the next time point	Only perception
4	Neighborhoods with more cohesion at one point in time will have fewer crimes in public space at the next time point	No
5	Neighborhoods with more cohesion at one point in time will have no effect on crimes in private space at the next time point	Yes
6	Neighborhoods with more burglaries at one time point will be more active to improve the neighborhood at the next time point	Yes
7	Neighborhoods with more public crime events at one time point will have lower cohesion and willingness to engage in informal social control at the next time point	No
8	Neighborhoods with more cohesion at one time point will have lower rates of frequent crime types at the next time point	No
9	Neighborhoods with more minor crime incidents at one time point will have lower levels of cohesion and willingness to perform informal social control at the next time point	No
10	Neighborhoods with more cohesion at one time point will have lower levels of perceived crime at the next time point	Yes
11	Neighborhoods perceiving more violent crime or frequent crime types will have lower cohesion at the next time point	Only violence



