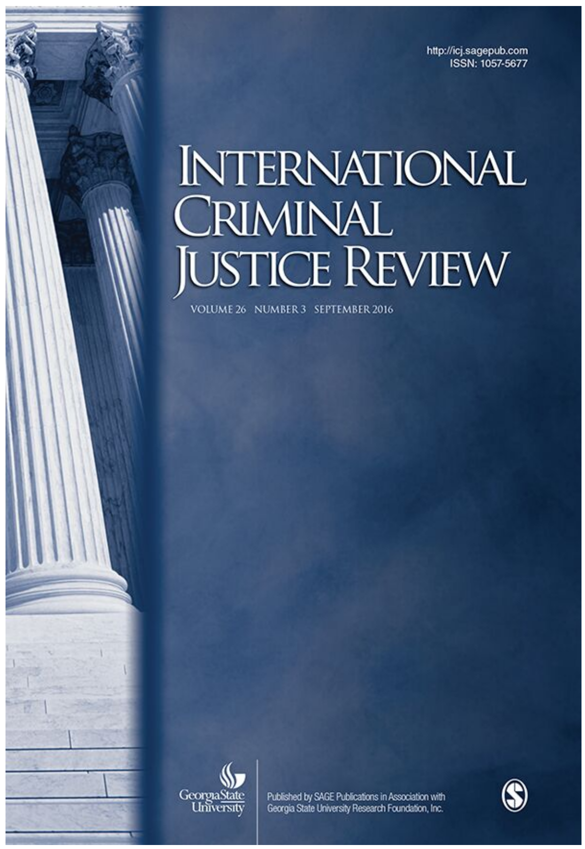
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Neighborhood-Level Effects on Trust in the Police: A Multilevel Analysis

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Abstract
From a multilevel perspective, the present study explores theoretical explanations for the causes of variations in neighborhoods' trust in the police. The study is designed to answer these questions: Why do some neighborhoods trust the police more than other neighborhoods? What makes a person living in a specific neighborhood to have more or less trust in the police, controlling for the person's personal views? To address these questions, the study analyzed survey responses from 1,024 residents selected from 25 communities across 5 regions in Ghana. Results revealed significant neighborhood variations in trust in the police in Ghana. Furthermore, a hierarchical linear modeling analysis revealed that the variations among the neighborhoods could be explained by their levels of disorder, income, and education. Findings from this study have both theoretical and practical implications and provide important insights for the police to improve upon their trustworthiness.

Keywords
neighborhood, police, trust, legitimacy, Ghana

Introduction

Understanding how residents' attitudes toward the police are shaped has become an important endeavor in recent years, since police institutions constantly face pressure to develop strong relationships with the public. Investigations into public attitudes have produced four distinct models explaining how citizens form their opinions about the police. The first is the experience with police model, which relates favorable attitudes to the quality of contacts citizens have with the police (Reisig & Parks, 2000). The second model, quality of life, presumes a connection between individuals' perceptions of their communities and how they think about the police. The demographic model relies on individual characteristics—age, sex, income, education, and race—to explain trusting relationships between the police and the public (Hurst & Frank, 2000; Weitzer & Tuch, 2002). Finally, the neighborhood context model links neighborhood conditions to individual assessment of

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the police (Reisig & Parks, 2000). Although the neighborhood context model makes a significant contribution to our understanding of how attitudes are developed, it is the least tested among the four models in attitudinal research.

The few studies that have tested neighborhood context model have examined the relationship between contextual variables and public attitudes toward the police and have mostly found negative effects on trust or confidence in the police (Hennigan, Maxson, Sloane, & Ranney, 2002; Reisig & Parks, 2000). Residents of communities characterized by poverty and inequality have been found to exhibit lower confidence in the police (Reisig & Parks, 2000). Moreover, a community's level of crime also predicts whether a person will have favorable or unfavorable perceptions of the police (Blumstein & Wallman, 2000; Hennigan et al., 2002; Jesilow, Meyer, & Namazzi, 1995; Maxson, Hennigan, & Sloane, 2003; Reisig & Parks, 2000; Sampson, Raudenbush, & Earls, 1997). These studies have consistently found a negative relationship between high crime rates and attitudes toward the police. Similarly, residential location significantly predicts an individual's level of satisfaction with police service (Schafer, Huebner, & Bynum, 2003).

Most of these studies suffer from a serious methodological issue that raises concern. Previous research adopted a microlevel approach in examining the effects of neighborhood variables on attitudes toward the police (see Ackerman et al., 2001; Macdonald & Stokes, 2006). The micro-level approach involved the use of multivariate regression techniques such as ordinary least square to ascertain the effects of neighborhood variables. This method is problematic because one is likely to violate the assumption of independence of errors, since individuals who live in the same neighborhood are often correlated with one another in other ways. To address this issue, this study uses a multilevel modeling approach to determine the influence of neighborhood-level factors on citizens' views about the police.

The main purpose of the current study is to further the discussion about the neighborhood context model. Using an aggregated survey of citizens to test the effects of neighborhood variables on trust in the police, the study attempts to answer these questions "Why do some neighborhoods trust the police more than other neighborhoods? What makes a person living in a specific neighborhood to have more or less trust in the police, controlling for the person's personal views?" Providing answers to these questions will facilitate intellectual discussion about effective ways of enhancing the citizen relationship with the police from a macro perspective. Fieldwork for this study was conducted in 2014 in 25 neighborhoods selected across 5 regions of Ghana, using a multistage sampling procedure. Overall, 1,024 residents participated in a study that lasted for 4 months.

Neighborhood Context Explanations

Studies examining the effects of neighborhood variables on citizens' perceptions of the police have considered the importance of neighborhood disorder in influencing perceptions. Neighborhood disorder has been found to reduce confidence in the police (Cao, Frank, & Cullen, 1996; Covington & Taylor, 1991; Dowler, 2002; Dowler & Sparks, 2008; Maxson et al., 2003; Sprott & Dood, 2009). Sprott and Dood (2009) compared the influence of perception of disorder on citizens' attitudes toward the police and the court system. They found that perception of disorder has a greater influence on citizens' attitudes toward the police than toward the courts. This means that if people consider disorder to be high in the community, they tend to have more negative attitudes toward the police than toward the courts. A plausible explanation could be that people consider crime and disorder prevention to be the work of the police and not the courts.

Maxson, Hennigan, and Sloane (2003) also observed that residents who perceived disorder in their neighborhoods expressed less approval of the police. Consistent with this finding is the observation that individuals' perception of quality of life in the neighborhood greatly influences their perception of the police (Dowler & Sparks, 2008). These authors further noted that the impact of disorder is greater than the impact of race on citizens' attitudes toward the police, suggesting that people formulate their attitudes about the police based on the level of quality of life in the community, which is affected by the level of disorder in the neighborhood (Skogan, 1990; Wilson & Kelling, 1982). Neighborhood disorder can cause serious crime if unchecked (Wilson & Kelling, 1982) as well as community deterioration (Skogan, 1990). Furthermore, these scholars have argued that if disorderly behavior is unchecked, members of the neighborhood become fearful and accordingly lose trust and confidence in the police for failing to prevent or stop disorder. Therefore, responding to neighborhood disorder is one way of preventing crime, reducing feelings of insecurity, and subsequently improving public attitudes toward the police.

In relation to the effect of fear of crime in a neighborhood on citizens' perception of the police, there has been limited effort, and the few studies have yielded largely inconsistent findings. Some studies have demonstrated that fear of crime has a negative relationship with attitudes toward the police (Cao et al., 1996; Cao, Stack, & Sun, 1998; Kaariainen, 2008; Reisig & Giacomazzi, 1998; Reisig & Parks, 2000; Reynolds, Semukhina, & Demidov, 2008; Sampson & Bartusch, 1998; Zhao, Scheiden & Thurman, 2002; Weitzer & Tuch, 2005). The more people fear crime in their neighborhoods, the less confidence they express in the police. Zhao, Scheiden and Thurman (2002) have argued that a decline in fear of crime ultimately leads to an increase in confidence in the police.

In addition, research on fear of crime has shown that citizens' fear of crime in the neighborhood has a greater influence on attitudes toward the police than do demographic variables (Cao et al., 1996). Similarly, Reynolds, Semukhina, and Demidov (2008) analyzed raw longitudinal data collected annually from 1998 to 2005 to examine the influence of fear of crime on trust in criminal justice institutions. Using structural equation modeling, the authors found that an increase in the level of fear of crime results in a decrease in the variance of trust in the criminal justice system. This further suggests that respondents who scored high on the fear of crime index reported low criminal justice trust. The result is consistent with the findings of Kaariainen (2008), who observed an inverse relationship between insecurity and trust in the police, suggesting that a feeling of insecurity in someone's neighborhood lowers the level of trust the person has in the police.

Research on fear of crime has discussed two basic types: generalized fear of crime and specific fear of crime (Clemente & Kleiman, 1976; Ferraro & LeGrange, 1987; Hale, 1996). Generalized fear denotes the fear that individuals have in general about their safety in the community and is normally measured by a single item asking respondents how worried they are about walking alone at night. Specific fear of crime denotes the fear of becoming a victim of specific types of crimes. Police researchers examining the influence of fear of crime on public attitudes toward the police have made attempts to investigate the specific impact of these two components and have obtained remarkable results. For example, Kautt (2011) examined the factors that influence citizens' attitudes toward the police and included two distinct measures of fear of crime. The first measure of fear of crime was a composite scale with five questions asking respondents how worried they were about becoming victims of crimes such as robbery, home break-ins, and sexual assaults. The second measure of fear of crime used a single item, asking respondents how safe they felt when walking alone after dark. These two measures of fear of crime, respectively, denoted specific fear and generalized fear. The author found that respondents who had higher scores on the fear of specific crime index rated the police excellent, while those who were worried about walking alone after dark were less confident in the police. These findings imply that fear of being robbed or sexually assaulted results in higher confidence in the police, because such individuals consider the police to be their protectors. This argument is in line with Block's (1970) argument that people who were fearful of crime would give the police extensive authority to stop and question suspected individuals. However, being generally afraid is linked to the inability of the police to protect individuals, hence results in lower confidence in the police. Kautt (2011) demonstrated that the effect of fear of crime on perceptions of the police largely depends on whether the fear is specific or general.

Contrary to studies, that have observed effects for the influence of fear of crime on public attitudes toward the police, some researchers claimed that fear of crime is unrelated to attitudes toward the police (Zevitz & Rettammel, 1990). These authors argued that no matter how fearful a person may be, the attitudes of that person toward the police will not be affected. This is surprising, considering the number of studies that have observed significant effects of fear of crime on citizens' attitudes toward the police. The inconsistencies among prior studies regarding the effect of fear of crime on perceptions are due to measurement and operationalization issues. For example, some studies used a single item to capture residents' general fear of crime in their neighborhoods. Using a single item, according to fear of crime researchers, is insufficient for capturing individuals' general fear of crime (Dubow, McCabe, & Kaplan, 1979; Ferraro & LeGrange, 1987). This study addresses this limitation using a scale of 5 items to measure residents' aggregate fear of crime on attitudes toward the police.

The above reviews illustrate the extent to which neighborhood variables can influence citizens' attitudes toward the police. To supplement these efforts, the current study examines the influence of the aforementioned contextual variables on Ghanaians' trust in the police by testing the following hypotheses:

Hypothesis 1: Citizens living in neighborhoods where there is higher rate of disorder will demonstrate lower levels of trust in the police.

Hypothesis 2: Neighborhood's level of fear of crime will negatively influence citizens' trust in the police. It is expected that individuals staying in neighborhoods where there are higher rates of fear of crime will report lower levels of trust in the police.

Effects of Other Variables

In addition to the effects of neighborhood factors, several other variables, mostly individual-level characteristics, have been found to predict perceptions of the police. For example, most studies have concluded that individuals' perception of how well they are treated by the police influences their subjective evaluation of the police (Gau, Corsaro, Stewart, & Brunson, 2012; Hinds, 2007; Hinds & Murphy, 2007; Mazerolle, Antrobus, Bennett, & Tyler, 2013; Mazerolle, Bennett, Antrobus, & Eggins, 2012; Mazerolle, Bennett, Davis, Sargeant, & Manning, 2013; Murphy, 2009; Reisig & Lloyd, 2009; Tyler, 2011; Tyler & Wakslak, 2004). Specifically, Gau, Corsaro, Stewart, and Brunson (2012) used hierarchical linear modeling (HLM) to examine the effects of macro-level factors on procedural justice and police legitimacy and found that, though macro-level factors such as concentrated disadvantage influenced perceptions of procedural justice, procedural justice remained the strongest predictor of legitimacy. This finding is consistent with the conclusion made by Hind and Murphy (2007) using an Australian sample.

Media exposure has also been observed to influence citizens' evaluation of the police. The public's negative ratings of the police as well as their dissatisfaction with the police have been linked to high media exposure and news consumption. Studies have shown that extensive media coverage of antisocial police behaviors such as use of force, brutality, and corrupt acts decreases people's confidence in the police (Dowler & Zawilski, 2007; Eschholz, Blackwell, Gertz, & Chiricos, 2002). The media therefore play significant role in shaping attitudes toward the police. Regarding the effect of ethnicity, previous studies have found that ethnicity is unrelated to perception of the police (Boateng, 2012).

Furthermore, studies have argued that individuals of lower socioeconomic status tend to have less favorable attitudes toward the police than those of higher socioeconomic status (Cao et al., 1996; Huang & Vaughn, 1996; Wu, Sun, & Tripplett, 2009). For instance, Wu, Sun, and Tripplett (2009) observed that lower class individuals were most likely to express lack of satisfaction with the police. However, some studies have also found contrarily that wealthy and highly educated individuals perceive the police less favorably than lower income and less educated persons (Murphy & Worrall, 1999; Weitzer & Tuch, 1999). In a recent comparative study that utilized both US and South Korean samples, Boateng, Lee, & Abess (2016) found that the less educated in both countries had higher confidence in their respective police institutions than highly educated individuals. Specifically, the authors observed that Americans with a high school education were more likely to have higher confidence in the police compared to those with more than a high school education. Likewise, South Koreans who possessed less than a high school education tended to have higher confidence in the police than those with high school education or higher.

To complicate matters further, other studies have argued that socioeconomic status and education are unrelated to attitudes toward the police (Correia, Reisig, & Lovrich, 1996; Parker, Onyekwuluje, & Murty, 1995; Priest & Carter, 1999; Ren, Cao, Lovrich, & Gaffney, 2005; Sims, Hooper, & Peterson, 2002). Correia, Reisig, and Lovrich (1996) observed that level of education did not significantly predict a person's trust in the police. Similarly, Priest and Carter (1999) found that income had no impact on perceptions of the police.

Despite the conflicting results of previous studies regarding the effects of socioeconomic status and education, no study has examined the effects of a neighborhood's average income and educational level on individuals' attitudes toward the police. To fill this void in the literature, the present study tests the following hypotheses:

Hypothesis 3: Citizens living in neighborhoods with lower average income will express lower levels of trust in the police.

Hypothesis 4: Citizens living in neighborhoods where there is higher percentage or number of residents possessing higher education will express higher levels of trust in the police.

Method

Study Population and Participants

The target population for this study included all individuals aged 18 years and above living in urban areas[1] of Ghana at the time of the survey administration. The survey collected information on people's opinions about the Ghana police and utilized a face-to-face interviewing technique to obtain relevant information from respondents selected randomly from five communities in the capital cities of five administrative regions. Each respondent participating in the study was selected from one household. Survey administration in all the five regions lasted approximately 4 months, from March to June 2014. Specifically, in each region, fieldwork, including training that was offered to research assistants, lasted 3 weeks. The remaining 4 weeks were spent on training of data entry personnel and the entry of data in Excel format.

Sampling Techniques and Procedure

To select respondents for participation in this study, a multistage cluster sampling method was adopted to ensure that a representative sample was obtained. The selection involved five stages. First, 5 regions were purposively selected from the 10 administrative regions in Ghana. It needs to be mentioned that some regions in Ghana are not diverse in terms of population. Some are highly homogeneous, whereas some are diverse because of tremendous economic and industrial activities. To obtain a representative sample, five regions with highly heterogeneous populations were selected. Based on this criterion, the following regions were selected for fieldwork: Ashanti, Greater

Accra, Central, Eastern, and Volta. Second, the capital city of each region was purposively selected for the study. There are two main reasons for focusing the study on the capital cities. The first is that regional capitals have more heterogeneous populations than other cities, due to economic and other commercial activities that are widespread in the capital cities. People migrate from other cities to the regional capitals for work or school. Second, police activities are presumed to be higher in the regional capitals than in the rest of the cities, mainly because of the widespread economic activities that attract people from different parts of the regions. Due to the intensity of enforcement efforts, it is believed that people in the regional capitals will experience the police more frequently than those in the other cities. Subsequently, such people are assumed to be in the position to evaluate the police fairly.

The third selection stage involved selecting five communities purposively from each regional capital in the five regions. Several reasons explain the purposive selection of the five communities. First, certain areas in Ghana are typically for commercial activities and are not residential areas. Hence, they are not useful for reaching populations. Second, some communities are reserved for specific government officials such as police officers, correctional officers, fire officials, and ministers. Including such areas in the study may bias the results, since respondents may not offer genuine responses to the questions asked. Third, some communities are inhabited solely by the rich or by the poor, and by including any of those communities in the study, one is bound to obtain partial views of the police, since the rich and the poor hold differential views of the police because of the differential treatment they receive. These reasons preclude random selection of the communities.

In the fourth stage, 250 households were randomly selected from the five communities (50 households from each community) in each capital city. According to Hailand (2003), a household constitutes one or more people who live in the same house and share meals or living accommodation. For the purpose of data collection, any single house where people did not share meals or living space was considered to constitute multiple households. In selecting the households, first, the researcher and the research assistants walked around the selected communities to count the number of households within a particular community. The idea was to prepare a list of all households in the community to facilitate random selection of the households. Once the list was prepared, a quota of 50 was used, and households were randomly selected until 50 were met. This system of selection was to ensure that every household in the community was given an equal chance of inclusion.

The final selection involved the selection of individual respondent from each household. In this selection, the use of the birthday methods—which involve selecting the individual from a household with the most recent or next upcoming birthday—was highly desirable, as they are quick, easy, and less intrusive as well as maximizing cooperation rates (Gaziano, 2005; Oldendick, Bishop, Sorenson, & Tuchfarber, 1988). Both the last-birthday and the next-birthday methods were used randomly in selecting the respondents. The birthday methods have been criticized for not being truly random; however, by applying both the last-birthday and the next-birthday selection methods in the same survey, the selection becomes truly random (Battaglia, Link, Frankel, Osborn, & Mokdad, 2008). The last-birthday method was used to select an individual who was at least 18 years old and was the last to celebrate his or her birthday in the household at the time of the survey administration. The next-birthday method was used to select an individual whose birthday was nearest to the date of the survey administration and was 18 years or older. Overall, 250 respondents were selected from each of the five administrative regions mentioned above, making the total sample 1,250 respondents.

Although the nature of the study did not necessarily require authorities' permission, as a matter of courtesy, I sought permission from the central police administration and the local councils in various regions where the study was conducted. This approach enabled authorities to be aware that the study was being conducted in the country. Questionnaires were administered to the selected individuals and were collected at the time of administration. This procedure ensured that the sampled individuals were the ones who actually filled out the questionnaire. Overall, 1,024 questionnaires out of the 1,250 were completed and collected, for a response rate of about 82%.

Table 1. Descriptive Statistics of Study Variables.[a]

Variables	Mean	*SD*	Minimum	Maximum
Outcome variable				
Trust in the police	14.67	4.46	5.00	25.00
Independent variables				
Individual-level predictors				
Education—more than senior high school	0.40	0.49	0.00	1.00
Ethnicity—Akan	0.50	0.50	0.00	1.00
Perception of fairness	16.78	4.53	6.00	30.00
Media exposure	3.44	1.04	1.00	5.00
Neighborhood-level predictors				
Aggregate fear of crime	12.19	1.36	10.13	15.16
Aggregate disorder	18.50	1.54	16.00	22.53
Aggregate income	0.36	0.11	0.18	0.60
Aggregate more than senior high school	0.41	0.17	0.16	0.85

[a]Total sample size is 1,024 residents and 25 neighborhoods.

Measures

Dependent variable. Trust in the police was an index variable, which was created from 5 items in the survey. Each item was measured using a 5-item Likert-type scale. These items were adopted from Sunshine and Tyler's (2003) questions with modifications to fit into the context of the present study. All 5 items had the same lead-in question, "For the following items, kindly indicate whether you agree or disagree: Overall, I trust the police in my neighborhood to protect lives and property; the police can be trusted to make decisions that are right for the people in your neighborhood; the police in your neighborhood are generally honest; I have absolute confidence that the police can do their job well; and the police care about the well-being of everyone they deal with." Response categories were (1) strongly disagree, (2), disagree, (3) undecided, (4) agree, and (5) strongly agree. A factor analysis with a maximum likelihood estimator indicated that all these items measured the same underlying construct (see Table 1). Therefore, the responses for all the items were summed to form an additive trust in the police scale. The scale had a mean of 14.67 ($SD = 4.46$) and an α value of .79, suggesting good internal reliability.

Independent variables. Four neighborhood variables were anticipated to influence trust in the police across neighborhoods. These included fear of crime, neighborhood disorder, aggregate level of education, and aggregate income. Descriptive statistics for the variables used in this study are presented in Table 1.

Fear of crime was measured using a 4-item Likert-type scale asking respondents to indicate whether they agreed or disagreed with the following statements: "I am afraid to walk in my neighborhood in the daytime," "I am afraid to walk in my neighborhood at nighttime by myself," "The level of security in my neighborhood is very low," and "Overall, I am afraid to be attacked in my neighborhood." The response categories were (1) strongly disagree, (2) disagree, (3) undecided, (4) agree, and (5) strongly agree. A factor analysis with a maximum likelihood estimator indicated that all these items measured the same underlying construct. As a result, the responses for the 4 items were summed together to form an additive fear of crime scale. The scale had a mean of 12.08 ($SD = 3.52$) and an α value of .64, suggesting acceptable internal consistency.

Neighborhood disorder measured the extent of neighborhood disorderly problems perceived by the respondents. It was measured using 8 items, 6 of which were used by Reisig and Parks (2000) to measure perceived incivility in their hierarchical analysis of satisfaction with police study. The8 items measured the extent of neighborhood problems: litter/trash, hanging around, vandalism, abandoned buildings, dirty gutters, gangs, unrepaired streetlights, and drug dealing. Each of these items had a 3-point response set (1 = *not a problem*; 2 = *minor problem*; and 3 = *major problem*). A factor analysis indicated that all these items measured the same underlying construct. Therefore, the responses were summed to form an additive neighborhood disorder scale. The scale had a mean of 18.50 (SD = 1.54) and an α value of .79, suggesting good internal reliability.

Neighborhood level of education was measured as an aggregation of respondents' level of education (see individual-level variables for details). The aggregate educational variable had a mean of 0.41 with an *SD* of 0.17.

Neighborhood average income was measured as an aggregation of respondents' annual household income. Respondents were asked to indicate their household's income per year (1 = less than Ghana Cedis (GHC) 5,000; 2 = 5,000–10,000; 3 = 10,001–15,000; and 4 = more than 15,000). These categories were later combined to form a dichotomous measure with 0 = GHC 10,000 or less (included initial Categories 1 and 2) and 1 = more than GHC 10,000 (included initial Categories 3 and 4). Any respondent who earned GHC 10,000 or below was considered a low-income earner.[2] The variable had a mean of 0.36 and an *SD* of 0.11.

Individual-level variables. Four individual-level variables were included in the HLM analysis to examine their effects on citizens' trust in the police. These included respondent's educational status, perception of fairness, media exposure, and ethnicity.

Level of education was measured by asking respondents to indicate their level of educational attainment at the time of survey administration: 1 = *no formal education*; 2 = *junior high school* ; 3 = *general education development or senior high school* (SHS); 4 = *higher national diploma*; 5 = *bachelor's degree*; and 6 = *graduate/professional degree*. These categories were later combined to form a dichotomous measure with 0 = *SHS or below* (included initial Categories 1, 2, and 3) and 1 = *more than SHS* (included initial Categories 4, 5, and 6).

Procedural fairness was measured using 6 Likert-type items adopted from Sunshine and Tyler (2003) and Tankebe (2009). The items, which were modified, asked respondents to indicate the frequency with which the police engaged in behavior consistent with procedural fairness in their neighborhood using the following response categories: (1) never, (2) almost never, (3) sometimes, (4) almost always, and (5) always. The items included "The police make decisions about how to handle problems in fair ways," "The police treat people fairly," "The police treat everyone in your neighborhood equally," "The police accurately understand and apply the law," "The police make decisions based upon facts, not their personal biases or opinions," and "The police give honest explanations for their actions to the people they deal with." A factor analysis revealed that all these items measured the same underlying construct. Therefore, the responses were summed to form a procedural fairness scale, which had a mean of 16.78 (SD = 4.53) and an α value of .77.

A single 4-point Likert-type item asking respondents to indicate the extent to which they heard news about the Ghana police through the mass media measured *media exposure*. The response categories included (1) never, (2) almost never, (3) sometimes, (4) almost always, and (5) always.

Ethnicity was initially measured as a categorical variable with 1 = *Akan*; 2 = *Ewe*; 3 = *Ga*; 4 = *Mole-Dagbon*; 5 = *others*. However, for the purpose of comparison, response categories were recoded as 0 = other (Ewe, Ga, Mole-Dagbon, and others) and 1 = *Akan*.

Plan of Analysis

HLM was the main modeling approach used in this study.[3] This approach allowed the researcher to examine the relative effects of individual-level (Level 1) and neighborhood-level (Level 2) variables on citizens' trust in the police. Four models were conducted, starting with the null

Table 2. Neighborhood-Level Variations in Aggregate Trust in the Police, Fear of Crime, Disorder, More Than High School, and Income.

Neighborhood	Trust	Fear of Crime	Disorder	More Than High School	Income
A	14.88 (3.67)	11.31 (3.57)	18.39 (4.22)	0.21 (0.42)	0.18 (0.39)
B	14.44 (4.04)	12.05 (2.99)	16.44 (3.55)	0.16 (0.37)	0.22 (0.42)
C	13.22 (5.90)	11.07 (3.19)	18.19 (4.23)	0.25 (0.44)	0.32 (0.47)
D	16.98 (3.70)	10.34 (3.61)	16.00 (4.60)	0.20 (0.41)	0.42 (0.50)
E	13.00 (5.06)	11.67 (3.14)	18.26 (3.82)	0.24 (0.43)	0.32 (0.48)
F	15.57 (4.99)	13.26 (3.83)	17.85 (4.28)	0.56 (0.50)	0.26 (0.44)
G	13.90 (4.77)	11.48 (3.83)	17.59 (3.29)	0.32 (0.47)	0.24 (0.43)
H	14.12 (4.30)	11.85 (3.95)	19.20 (3.12)	0.42 (0.50)	0.31 (0.47)
I	14.74 (4.08)	12.72 (3.80)	18.94 (3.86)	0.85 (0.37)	0.60 (0.50)
J	15.22 (3.59)	11.48 (3.97)	17.17 (3.68)	0.69 (0.47)	0.22 (0.42)
K	17.47 (3.91)	11.58 (2.72)	16.87 (3.65)	0.35 (0.48)	0.58 (0.50)
L	12.63 (4.06)	10.13 (3.43)	21.07 (3.23)	0.38 (0.49)	0.41 (0.50)
M	11.40 (3.65)	10.74 (3.18)	22.53 (2.61)	0.51 (0.51)	0.38 (0.49)
N	11.04 (2.90)	12.94 (3.27)	20.72 (3.07)	0.21 (0.41)	0.34 (0.48)
O	13.12 (3.56)	12.17 (3.16)	21.53 (3.21)	0.37 (0.49)	0.32 (0.47)
P	12.92 (4.76)	10.47 (3.62)	17.51 (3.44)	0.31 (0.47)	0.35 (0.49)
Q	14.80 (4.61)	12.00 (3.66)	18.13 (3.92)	0.35 (0.49)	0.44 (0.51)
R	13.86 (4.30)	11.83 (3.46)	18.75 (4.11)	0.50 (0.51)	0.34 (0.48)
S	15.57 (3.59)	12.18 (3.06)	18.61 (2.87)	0.52 (0.51)	0.40 (0.50)
T	15.81 (4.23)	11.71 (3.61)	18.26 (3.17)	0.24 (0.44)	0.46 (0.51)
U	18.20 (2.80)	15.16 (1.62)	17.51 (2.44)	0.48 (0.51)	0.57 (0.53)
Z	16.70 (3.09)	14.58 (2.68)	18.50 (3.55)	0.53 (0.50)	0.50 (0.51)
W	16.86 (3.40)	13.36 (2.88)	18.00 (2.88)	0.40 (0. 50)	0.36 (0.50)
X	18.00 (4.08)	13.80 (3.03)	18.45 (3.71)	0.61 (0.50)	0.33 (0.49)
Y	16.00 (2.22)	14.88 (2.00)	17.93 (2.17)	0.56 (0.51)	0.25 (0. 50)
F-score	9.61	6.25	8.13	5.35	1.81
p-Value	<001	<001	<001	<001	<001
η^2	.193	.135	.180	.118	.056

Note. Actual names of the neighborhoods have been replaced with alphabetical letters due to confidentiality reasons. Standard deviations are in parentheses. η^2 = effect size.

(intercept only) model with no predictors, followed by the total effect model, which included only Level-1 individual variables with no Level-2 variable. The third model, the contextual effect model, included both Level-1 and Level-2 variables, which were grand mean centered. Finally, the fourth model was the between effect model, which included Level-1 group mean-centered variables and Level-2 grand mean-centered variables to determine the between-neighborhood effect on trust. However, before running these models, an analysis of variance (ANOVA) was conducted to determine whether the neighborhoods being studied varied by their level of trust in the police as well as by level of fear of crime, education, and income.

Results

Exploring Significant Differences Among Neighborhoods

To explore significant differences among the 25 neighborhoods on the 5 dimensions, ANOVA and effect size calculations were conducted (see Table 2). The first column represents the results for neighborhoods' aggregate trust in the police. The test revealed significant group differences ($F = 9.610$, $df = 24$, $p < .001$).[4] A post hoc Bonferroni comparison was conducted to determine each group impact. This analysis indicated significant mean differences among the neighborhoods, suggesting that the neighborhoods did differ in terms of their levels of trust in the police. The effect size calculations ($\eta^2 = .193$) indicate that the neighborhood variable explains 19% of the variance in trust in the police.

The second column presents the results for the neighborhoods' aggregate levels of fear of crime. With an effect size of .135, neighborhood explains about 14% of the variance in fear of crime. The ANOVA test revealed significant group differences ($F = 6.25$, $df = 24$, $p < .001$). Since the F-test was significant, a post hoc Bonferroni comparison was conducted to determine each group impact. The analysis revealed significant mean differences, indicating that the neighborhoods differed in terms of their aggregate levels of fear of crime.

The third column presents the results for the neighborhoods' aggregate levels of neighborhood disorder. The test revealed significant group differences ($F = 8.13$, $df = 24$, $p < .001$). This suggests that the 25 neighborhoods did differ in terms of their aggregate levels of disorder. A post hoc Bonferroni comparison revealed significant mean differences among the groups. For example, the analysis demonstrates that neighborhoods A and M, A and O, B and L, B and M, B and N, B and O, C and M, C and O, D and L, D and M, and D and N significantly differ. The effect size calculations ($\eta^2 = .180$) indicate that the neighborhood variable explains 18% of the variance in disorder.

Similarly, ANOVA of the neighborhoods' aggregate rates of residents possessing more than high school education (Column 4) revealed significant group differences ($F = 5.35$, $df = 24$, $p < .001$). A post hoc Bonferroni comparison conducted revealed significant mean differences among the neighborhoods, suggesting that the neighborhoods differed in terms of average number of individuals who had attained more than high school education. Neighborhood explains about 12% of the variance in more than high school education.

Finally, Column 5 presents the results for the neighborhoods' average income. The test revealed significant group differences ($F = 1.81$, $df = 24$, $p < .001$). A post hoc Bonferroni comparison conducted revealed significant mean differences among the groups. The effect size calculations ($\eta^2 = .056$) suggest that the neighborhood variable explains 6% of the variance in aggregate income.

Overall, the ANOVA on trust in the police indicates significant neighborhood variations. The question left to be answered is could these variations be due to the variation that exists among the neighborhoods in terms of their aggregate rates of fear of crime, disorder, education, and income? This question is explored in the HLM analysis.

Exploring Contextual Effects on Trust in the Police

To examine contextual effects on citizens' trust in the police, a multilevel modeling technique was employed using HLM software Version 6. Four models were created and the results are presented in Table 3. Model 1 was the null model, which included only the grand mean-centered outcome variable (trust in the police). The results revealed that the group mean level of trust in the police was positive and higher than the grand mean (14.80 vs. 14.67). The model was significant ($t = 38.63$, $p < .001$), indicating that there was a significant variation in trust in the police at Level 2.[5]

In Model 2, four Level-1 grand mean-centered variables—Akan ethnicity, more than high school education, perception of procedural fairness, and media exposure—were added to determine their total effect on citizens' trust in the police. The intercept indicates that the levels of trust possessed by citizens who were Akans, had attained more than SHS education, perceived the police to be fair, and had less frequent media exposure were slightly above the group mean (14.69***). The Akan variable was significant ($t = 2.37$, $p < .05$), and with a coefficient of 0.63, indicating that citizens who belonged to the Akan ethnic group had more trust in the police than those who belonged to other groups. Similarly, more than SHS was significant ($t = 2.24$, $p < .05$) and with a positive coefficient,

Table 3. Hierarchical Linear Model Analysis of Trust in the GPS.[a]

Variables	Model 1	Model 2	Model 3	Model 4
	Null	Total Effect (Level 1 Grand)	Contextual Effect (Levels 1 and 2 Grand)	Between Effect (Level 1 Group and Level 2 Grand)
Intercept	14.80 (0.38) [38.63]***	14.69 (0.23) [63.21]***	14.70 (0.17) [86.56]***	14.77(0.22) [67.42]***
Level 2: Neighborhood				
Mean fear of crime	—	—	0.02 (0.13) [0.18]	0.50 (0.18) [2.82]**
Mean disorder	—	—	−0.40 (0.10) [−3.96]***	−0.79 (0.15) [−5.39]***
Mean income	—	—	1.31 (1.84) [0.71]	4.11 (1.96) [2.10]*
Mean more than SHS	—	—	3.06 (1.29) [2.73]*	1.79 (1.83) [0.98]
Level 1: Individual				
Akan	—	0.63 (0.28) [2.37]*	0.55 (0.27) [2.02]*	0.56 (0.30) [1.88]*
More than SHS	—	0.39 (0.17) [2.24]*	0.30 (0.18) [1.63]	0.30 (.18) [1.61]
Procedural fairness	—	0.57 (0.03) [18.42]***	0.56 (0.03) [17.97]***	0.60 (0.03 [17.73]***
Media exposure	—	−0.26 (0.14) [−1.90]*	−0.23 (0.14) [−1.73]*	−0.26 (0.14) [−1.89]*
Variance components				
Level 1 (r)	16.43	10.98	10.97	10.97
Level 2 (u_0)	3.38	1.09	0.62	1.19
Pseudo R^2				
Level 1	—	33%	33%	33%
Level 2	—	68%	82%	65%
Model fit statistics				
Deviance statistics	5,632.802	4,699.294	4,684.193	4,693.678
No. of Est.	2	2	2	2

Note. GPS = Ghana Police Service. SHS =Senior High School. Standard errors in parenthesis, *t*-ratios in bracket.
[a]Model Specification: Model 1: $TRUST_{ij} = \gamma_{00} + u_{0j} + r_{ij}$; Model 2: $TRUST_{ij} = \gamma_{00} + \gamma_{10}{*}AKAN_{ij} + \gamma_{20}{*}POSTSENI_{ij} + \gamma_{30}{*}PROCEDUR_{ij} + \gamma_{40}{*}MEDEX_{ij} + u_{0j} + r_{ij}$; Model 3: $TRUSTSCA_{ij} = \gamma_{00} + \gamma_{01}{*}FEARCRIM_j + \gamma_{02}{*}DISORDER_j + \gamma_{03}{*}INCOME\_M_j + \gamma_{04}{*}POSTSENI_j + \gamma_{10}{*}AKAN_{ij} + \gamma_{20}{*}POSTSENI_{ij} + \gamma_{30}{*}PROCEDUR_{ij} + \gamma_{40}{*}QJ12_{ij} + u_{0j} + r_{ij}$; Model 4: $TRUST_{ij} = \gamma_{00} + \gamma_{01}{*}FEARCRIM_j + \gamma_{02}{*}DISORDER_j + \gamma_{03}{*}INCOME\_M_j + \gamma_{04}{*}POSTSENI_j + \gamma_{10}{*}AKAN_{ij} + \gamma_{20}{*}POSTSENI_{ij} + \gamma_{30}{*}PROCEDUR_{ij} + \gamma_{40}{*}MEDEX_{ij} + u_{0j} + r_{ij}$.
*$p < .05$. **$p < .01$. ***$p < .001$.

citizens who possessed more than SHS education had more trust in the police than citizens who possessed SHS education or less.

In addition, procedural fairness had a significant influence on trust in the police ($t = 18.42$, $p < .001$), and had a positive coefficient of 0.57, meaning a unit increase in perception of procedural fairness resulted in a 0.57 increase in trust in the police. Finally, media exposure was equally significant ($t = -1.90$, $p < .05$), and the negative coefficient (−0.26) indicated that citizens who frequently experienced the police through the media had lower trust in the police.

Model 2, which contained only individual-level variables, explained a decent amount of variability in trust in the police at both Level 1 and Level 2. Specifically, the model explained 33% of the variance in trust in the police at Level 1 and 68% at Level 2.

To determine the Level 2 contextual effect and the Level 1 within-neighborhood effect, four grand mean-centered variables—mean (aggregate) fear of crime, mean (aggregate) disorder, mean (aggregate) income, and mean (aggregate) more than high school—were added in Model 3. The intercept indicates that citizens who were Akans; perceived the police to be fair; had less frequent media exposure; and lived in neighborhoods with the grand mean levels of fear of crime, disorder, income, and more than high school education possessed levels of trust in the police that were slightly above the group mean (14.70). Mean (aggregate) disorder was significant ($t = -3.96$, $p < .001$) and the coefficient was negative (−0.40). The negative coefficient suggests that irrespective of individual perceptions of disorder, citizens who lived in neighborhoods with greater aggregates of disorderly conduct tended to have lower trust in the police compared to those who lived in neighborhoods with lower aggregates of disorderly behavior. Similarly, mean (aggregate) more than SHS education was significant ($t = 2.73$, $p < .05$), suggesting that, regardless of individual educational background, citizens who lived in neighborhoods with a greater proportion of residents possessing more than SHS education tended to have higher trust in the police than those who lived in neighborhoods with few residents having more than SHS education.

Moreover, three Level-1 grand mean-centered variables remained significant in Model 3 after controlling for Level 2 contextual variables. The Akan variable was significant ($t = 2.02$, $p < .05$), and the coefficient of 0.55 indicates that citizens who belonged to the Akan ethnic group had higher trust in the police than those who belonged to other groups. Furthermore, procedural fairness had a significant influence on trust in the police ($t = 17.97$, $p < .001$), with a positive coefficient of 0.56; a 1-unit increase in perception of procedural fairness resulted in a 0.56 increase in trust in the police. In addition, media exposure was significant ($t = -1.89$, $p < .05$), indicating that citizens who frequently experienced the police through the media had lower trust in the police. This model also explained a fair amount of the variability in trust in the police at both levels. At Level 1, the model explained 33% of the variance in trust in the police, and at Level 2, it significantly explained 82%.

To examine between-neighborhood effects, four group-mean-centered Level-1 variables and four grand mean-centered Level 2 variables were added in Model 4. The intercept indicates that citizens who were Akans; perceived the police to be fair; had less frequent media exposure; and lived in neighborhoods with the grand mean levels of fear of crime, disorder, income, and more than high school education possessed levels of trust in the police that were slightly above the group mean (14.77). Three grand mean-centered Level 2 variables were found to influence trust in the police significantly. Mean (aggregate) fear of crime was significant ($t = 2.82$, $p < .01$) and the coefficient was positive (0.50). The positive coefficient suggests that, irrespective of individual perceptions of fear of crime, citizens who lived in neighborhoods with greater aggregates of fear of crime tended to have higher trust in the police compared to those who lived in neighborhoods with lower aggregate fear of crime.

Mean (aggregate) disorder was significant ($t = -5.39$, $p < .001$) and the coefficient was negative (−0.79), implying that, irrespective of individual perceptions of disorder, citizens who lived in neighborhoods with a greater aggregate level of disorderly conduct tended to have lower trust in the police compared to those who lived in neighborhoods with lower aggregates of disorderly behavior. Similarly, mean (aggregate) income was significant ($t = 2.10$, $p < .05$), suggesting that, regardless of individual income levels, citizens who lived in neighborhoods with high average income (or earnings) tended to have higher trust in the police than those who lived in neighborhoods with low average income.

Likewise, three Level 1 grand mean-centered variables remained significant in Model 4 after controlling for Level 2 contextual variables. The Akan variable was significant ($t = 1.88$, $p < .05$), and the coefficient of 0.56 shows that citizens who belonged to the Akan ethnic group had higher trust in the police than those who belonged to other groups. Furthermore, procedural fairness had a significant influence on trust in the police ($t = 17.73$, $p < .001$) and had a positive coefficient of 0.60; a 1-unit increase in perception of procedural fairness resulted in a 0.60 increase in trust in the police. In addition, media exposure was significant ($t = -1.89$, $p < .05$), indicating that citizens who frequently experienced the police through the media had lower trust in the police. This model explained 33% of variance in trust at the individual level and 65% at the neighborhood level.

Discussion

The purpose of the present study was to explore contextual explanations for the varied levels of trust among different neighborhoods. The study aimed to answer these questions: Why do some neighborhoods trust the police more than other neighborhoods? What makes a person living in a specific neighborhood place more or less trust in the police, controlling for the person's personal views? The findings revealed significant effects of community characteristics in explaining variations in levels of trust across neighborhoods. The 25 neighborhoods studied differed significantly in their levels of trust in the police. Some neighborhoods had higher trust in the police, while others had lower trust in the police.

Using advanced multilevel modeling, the study addressed these questions by observing the effects of three contextual variables on neighborhoods' confidence in the police. Community rate of disorder exerted a significant negative influence on the level of trust of people living in the area, controlling for their individual characteristics, such as ethnic background, perception of fairness, and exposure to the media. This result implies that Ghanaians who live in neighborhoods with higher rates of disorder will express lower trust and confidence in the police irrespective of their perceptions of the police. Citizens' levels of trust, therefore, vary based on the area where they live. The observation is consistent with prior studies that found similar results in other social contexts (Dowler & Sparks, 2008; Maxon et al., 2003; Sprott & Dood, 2009). Maxon et al. (2003) found that residents who believed disorder was on the increase in their neighborhoods expressed disapproval of the police and were more critical of how the police performed their duties.

Additionally, community levels of income and education were also found to affect neighborhood level of trust in the police. The effect of aggregate community income was positive, indicating that neighborhoods possessing higher average income had greater trust in the police compared to those with lower average income. At the individual level, citizens who reside in higher average income neighborhoods demonstrated favorable attitudes toward the police regardless of their opinions of the police. Similarly, neighborhood level of education influenced how citizens perceived the police. People who lived in neighborhoods where the majority of the residents were highly educated were more likely to show greater confidence in the police.

Possible explanations for these results could be seen from the assumptions of the conflict theory (see Chambliss & Seidman, 1971). Supporters of this theory have argued that the interests of the dominant class—which in this case would be the highly educated and high-income earners in the society—are protected by the police, whereas the lower class individuals—the less educated and lower income earners—are continuously monitored by law enforcement officials (Chambliss &

Seidman, 1971; Das, 1983). It is, therefore, obvious that communities where the highly educated and high-income citizens live will receive favorable treatment from the police, which might lead to a favorable trusting relationship between the two groups. Conversely, areas where lower class citizens are concentrated may experience biased treatment and aggressive enforcement strategies that might deteriorate the relationship between the police and such communities. According to researchers (Gabbidon & Jordan, 2013; Weitzer & Tuch, 2006; Wu et al., 2009), this deteriorated relationship may lead to the expression of negative views about the police. This line of reasoning also fits well into the ecological contamination explanation of police action on the street (Alpert & MacDonald, 2001; Kane, 2002). These authors have argued that police tailor their behavior based on the specific neighborhoods they serve. Therefore, if police officers work in dangerous neighborhoods, they are tempted to use force more often.

The last neighborhood variable that had a significant influence on community trust in the police was average fear of crime in the neighborhood. Interestingly, the effect was positive, indicating that neighborhoods with high rates of fear of crime had higher confidence in the police. Stated differently, residents who lived in neighborhoods where fear of crime was high tended to have greater confidence in the police irrespective of their personal opinions of the police. This finding is surprising, given the abundant studies that have observed a negative relationship between fear of crime and attitudes toward the police at the individual level (Cao et al., 1996; Kaariainen, 2008; Zhao et al., 2002). These authors believed that an increase in fear of crime would result in a decrease in attitudes. However, one might also be tempted to think that, at the community level, if citizens perceive fear of crime to be high in communities where they reside, they may tend to see the police as the only source of security. To ensure maximum security and protection, citizens inadvertently develop greater trust in the police.

Understanding the Effects of the Neighborhood Variables in Ghana

The observed effects of the community variables in the Ghanaian context can be better understood with an exploration of the social development prevailing within specific neighborhoods in Ghana. Social change—modernization, industrialization, and urbanization—has led to a complex division of labor, migration, and production and distribution of goods and services (Amuzu & Leitmann, 1991; Asiama, 1984) as well as altering the patterns of people's routine activities and lifestyles (Appiahene-Gyamfi, 2002). Moreover, the process of social change has widened the gap between the rich and the poor and has created a phenomenon known as persistent differentiated neighborhoods in modern Ghana. The rich and the poor live in different locations with different levels of development. It can be argued that differentiated neighborhoods existed during the colonial days, but the problem today is worse than what existed in the past. This phenomenon has serious implications for policing, since police officers tend to treat people differently based on where they stay or work. Residents of affluent neighborhoods, by virtue of their influence and power, are accorded much respect and offered friendly treatment by the police. In contrast, those who live in poor neighborhoods—popularly known as ghettos or slums—are treated harshly and sometimes with no respect (Appiahene-Gyamfi, 2002).

Residential neighborhoods in Ghana are broadly categorized as low-income, middle-income, and high-income areas. These categories are differentiated primarily by factors such as housing conditions, availability of facilities, and level of security. For example, in the Accra metropolitan area, housing conditions in the low-income neighborhoods are depressed with social and engineering infrastructure. Buildings in these neighborhoods are usually dilapidated and often made of poor quality materials: mud, untreated timber, and zinc roofing sheets for walling (see Accra Metropolitan Assembly website: www.ama.ghanadistricts.gov.gh).

According to the Assembly, about 58% of the city's population reside in the low-income areas, such as Osu, Nungua, Chorkor, Jamestown, Nima, Abeka, and Sukura, to mention a few. These areas in the city are notoriously characterized by inadequate housing infrastructure, poor drainage systems, erosion, and high population concentration. In addition, layouts are haphazard and there are no proper streets running through the neighborhoods. Houses and buildings are scattered everywhere, and there is no room for easy maneuvering. These kinds of layouts create space for illicit activities to flourish but do not support police activities such as bike, vehicular, and foot patrols (Appiahene-Gyamfi, 2003). The majority (if not all) of the residents in the poor neighborhoods do not have access to telephones at home, and as Appiahene-Gyamfi (2003) noted, the lack of access to telephones by residents prevents crime reporting to the police. To complicate matters, most of the poor neighborhoods in Ghana are located far from police stations, further limiting residents' ability and desire to physically walk in to make complaints or report to the police.

Comparatively, the middle-income areas are generally planned, and buildings are made with quality materials. Housing conditions are much better than those in the low-income neighborhoods, and residents in these neighborhoods make up 32% of the city's population. The middle-income neighborhoods include areas such as Kanda Estates, Abelempke, Tesano, and Dansoman Estates. Most buildings in these areas are government-owned and are mainly occupied by government workers. The areas are semiplanned with streets that sometimes support police operations.

The high-income areas, also called the affluent neighborhoods, are well planned and structured and have well-developed infrastructure. Residents in these neighborhoods form 10% of the city's population and are mostly the wealthiest people in the society—academics, businessmen and businesswomen, politicians, foreigners, diplomats, and those who have lived in either the United States or Europe. Because of their wealth, residents in these neighborhoods enjoy maximum security, often provided either by the police security apparatus or by private security agency. Appiahene-Gyamfi (2003) observed that homes with police or private security guards experienced fewer burglary incidents. Furthermore, the patterns of layout in the rich neighborhoods support police patrolling activities, and as a result, there is an increased police presence at all times. Additionally, residents have access to telephones, which makes it easy for them to call the police to report criminal incidents.

Situations in all three categories of neighborhoods differ and have different effects on residents' relationship with the police. For instance, the prevailing circumstances in the low-income neighborhoods—no police presence and not being able to reach the police, coupled with ill treatment from the police—significantly and negatively affect residents' relationship with and attitudes toward the police. It is, therefore, not surprising that residents in such neighborhoods will express negative feelings and distrust in the police service. Conversely, the rich, who enjoy maximum security, are recognized with respect and can easily reach the police, have different, mostly favorable attitudes toward the police in Ghana.

The present study is not without limitations, and these must be acknowledged. First, the study examined contextual factors influencing trust in the police and attempted to generalize its findings to the entire population of Ghana. However, the study excluded the opinions and attitudes of individuals living in the rural areas of Ghana, hindering the study's ability to generalize its findings to the entire population. In the light of these limitations, it is recommended that future research be conducted to examine the opinions of individuals living in rural areas of Ghana about the Ghana police. Second, the study failed to examine all the relevant neighborhood variables that have been found by research to influence trust in the police. As a result, the effects of variables such as neighborhood crime rates, unemployment rates, and proximity of police stations on trust in the police are still not known. Furthermore, important individual-level factors such as gender, age, and race were not included in the current analysis, given their influence on trust in the police. It is therefore suggested that future research should be completed to take into consideration these and other factors not examined in this study.

Despite these limitations, the findings of this study help to answer crucial questions pertaining to individual and community attitudes toward the police. The findings offer both theoretical and practical implications. Theoretically, the findings offer empirical justification for the use of neighborhood-level variables in explaining citizens' attitudes toward the police. Specifically, the findings help to address questions such as why attitudes toward the police vary from neighborhood to neighborhood and why individuals with the same perceptions of the police might have different levels of trust and confidence in the police.

Practically, the findings can offer meaningful indications for the police to develop better policies directed at establishing cordial relationship with the community they serve. Analysis based on the study's data indicates that people who live in communities with low educational attainment, low annual income, and high disorder rates will inadvertently develop negative attitudes toward the police irrespective of their individual perceptions. Although the police cannot address issues pertaining to low income and educational attainment, they can certainly control disorderly conducts in the neighborhoods in two ways. First, the police must be empowered to enforce city ordinances so that minor disorderly conducts that are not illegal could be punished. Second, police administrators must increase the presence of the police in areas where disorder is high and consider fighting all forms of disorderly behaviors as operational priority. Zero-tolerance policy needs to be implemented to fight neighborhood disorder effectively. In addition to reducing disorder, each community must have access to educational facilities to boost the education needs of its residents.

The present study represents one of the few efforts to use mixed model approach to understand how citizens develop their perceptions about their local police and recommends that police departments and the communities need to continue efforts to improve police–citizen relationship. Reducing disorderly conduct and its associated fear not only enhance the image of the police in the community but also foster an environment that promotes social cohesion among community members.

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Notes

1. According to the 2010 Population and Housing Census (Ghana), an urban is a locality with 5,000 or more people.
2. In terms of the US dollar, Ghana Cedis 10,000 is equal to approximately US$3,000.
3. Some researchers believe that using fewer than 30 Level 2 units in mixed models is appropriate and does not bias the results (e.g., see Browne and Draper, 2000). It is based on this argument that the author strongly believes the models created are stable and have no issue.
4. A separate set of analysis of variances also revealed significant differences among the five cities (where these neighborhoods were selected) regarding their aggregate levels of trust, fear of crime, disorder, education (more than high school), and average income. The results of these analyses are not provided.
5. Further, by examining the final estimation of variance components, it was revealed that the assumption of the independence of errors has been violated since the Intercept 1 was significant ($\chi^2 = 231.715$, $p < .001$). This calls for the need to run a multilevel model instead of running an ordinary least square regression to test contextual effects.

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Subnational Predictors of Racially Motivated Crime: A Cross-National Multilevel Analysis

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Abstract

This study draws upon theories of intergroup prejudice and bigoted violence to examine the effects of subnational correlates on the levels of racially motivated crime across different regions in four European countries between 1997 and 2013. To facilitate comparisons of hate crime across different nations, we estimate multilevel panel rate models where time is nested within the subnational units. The results reveal a significant and negative effect of the size of the foreign-born population on racially motivated crime, which is consistent with the power-differential hypothesis. In addition, we find that there is a concave curvilinear relationship between the size of the foreign-born population and racially motivated crime. The study concludes by discussing the role of contextual factors in predicting crime motivated by bias.

Keywords

Western Europe, comparative crime/justice, Eastern Europe, race and crime/justice, other

Introduction

The past three decades have seen a growing interest in the phenomenon of hate crime, which is widely understood as "unlawful, violent, destructive, or threatening conduct in which the perpetrator is motivated by prejudice toward the victim's putative social group" (Green, McFalls, & Smith, 2001, p. 480). Although there is in fact a long history of violence committed against minority groups—consider the holocaust (Goodey, 2008) or the U.S. racial riots in the early 1930s—it is only over the course of recent years that scholars, practitioners, and policy makers on both sides of the Atlantic have begun to engage in research focused around the issue of hate crime (Garland & Chakraborti, 2012). In response to growing concern about hate crime, the U.S. congress passed the Hate Crime Statistics Act of 1990, which mandated systematic data collection on the part of law agencies (Perry, 2010). The European Union (EU), meanwhile, founded the European Monitoring

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Centre on Racism and Xenophobia in 1997, which was supposed to collect and analyze data on the prevalence and development of anti-Semitism and racist and xenophobic crimes at the European level (European Union Agency for Fundamental Rights, 2007—henceforth, referred to as the FRA).

Although various countries have taken legislative steps to enhance hate crime reporting and improve the collection of data related to crimes motivated by racism, xenophobia, and related intolerances (FRA, 2013), levels of racist crime seem to have generally increased over the past decades (Björgo & Witte, 1993; see also Garland & Chakraborti, 2012). In the 2010–2011 period, for instance, statistics indicate increases in racially motivated crimes in Belgium, Denmark, Finland, Germany, Lithuania, Luxemburg, Poland, Spain, Sweden, and the Netherlands (FRA, 2013). Data also indicate that Finland, France, and Sweden have experienced increases in the levels of Islamophobic/anti-Muslim crime, while Germany, Poland, and Sweden have seen an upward surge in extremist crime during the same time period (FRA, 2013).

That increases in the amount of officially recorded hate crime are not isolated to one or several nations but instead seem to be widespread raises important questions regarding crime motivated by bias. What factors account for increases in the levels of hate crime across different nations? More specifically, what factors may account for cross-regional and cross-county variations in the incidence of hate crime across different nations? How do the determinants of hate-motivated crimes vary depending on geographic unit of analysis? This study aims to address these questions by investigating the effects of subnational correlates on the levels of racially motivated crime rates across different regions and counties in four European countries between 1997 and 2013. Using pooled cross-sectional, time-series data on officially recorded racist crimes, we examine whether the regional and county levels of racially motivated crime in these countries' subnational jurisdictions have been influenced over time by the relative size of the foreign-born population and economic conditions. We focus on racially motivated crimes because data on this type of offense are collected more often than data related to crimes motivated by other biases (FRA, 2013; Goodey, 2008). Although the precise definitions vary considerably from one nation to the next—a fact addressed in more detail in subsequent sections of this article—the term racially motivated crime is commonly conceptualized as bias-motivated crime committed against a victim because of his or her membership (or perceived membership) in a racial group (see Garland & Chakraborti, 2012; Green et al., 2001). At a general level, then, the dependent variable for the analyses undertaken herein can be understood as racist hate crime as understood within the societal context.

Our study is distinctive in several aspects. First, at present, only a limited body of work has utilized a comparative, cross-national approach to examine violence committed against minorities (Brustein & King, 2004; Dancygier, 2010), and comparative research regarding officially recorded hate crimes is, to our knowledge, almost nonexistent. None of the studies on hate crime that currently exist has also examined the effects of subnational-level factors on official hate crime rates over time. The paucity of comparative, cross-national research on this topic is critical because, as noted by Perry (2003), "comparative studies ... will allow us to uncover the constant in hate crime, the broad constellations of conditions that make such violence likely—conditions like rapidly shifting demographics, economic downturns or uncertainty, or volatile political discourse, for example. Thus, these analyses may help us to build theoretical accounts" (p. 50). The implication, here, is that by utilizing a comparative research methodology, we may deepen our understanding of the forces which contribute to violence against minorities. Surely, developing such an understanding is a critical step in the fight against such crime.

In this study, we heed Perry's (2010) call and utilize a cross-national approach to examine the effects of subnational correlates on the levels of racially motivated crime. We do so with direct reference to the theories of intergroup crime and violence that emphasize the role of economic conditions and minority-group size in intergroup prejudice and crime (Blalock, 1967). Prior studies have mainly examined their effects in the United States (Green, Strolovitch, & Wong, 1998; Lyons, 2007). Little is known, however, about their relevance in the cross-national domain. As such, this study is well positioned to fill a current informational gap.

The present study is also timely in light of recent demographic changes, economic downturns, and contentious political debates. Over the past decades, Europe has witnessed unprecedented levels of immigration and economic instability, and there is something of a paradox playing out on the world stage: Although values related to democracy and equality continue to thrive in this continent, minority groups increasingly become victims of bigoted crimes (Garland & Chakraborti, 2012). Minorities, who are often viewed as a cause of economic turmoil, sometimes become a target in political debates. It is still unclear, however, exactly how the foreign-born population size and economic conditions contribute to increased levels of hate-motivated crimes across Europe. This study seeks to enhance our understanding of these forces and increase our knowledge about hate-motivated crime.

Research on Hate Crime in Western Nations

The existing body of empirical work on hate crime is rather scarce (Green et al., 2001), and as noted above, only a limited subset of studies have utilized a comparative, cross-national approach to investigate violence committed against minorities (Brustein & King, 2004; Dancygier, 2010). The dearth of existing research is likely due at least in part to data limitations. In most European nations, data collection systems on hate crime are relatively new, are often inadequate, and are limited in various ways (Goodey, 2008). Countries also sharply diverge in terms of how they understand and conceptualize hate crime and differ with regard to the determinations that have been made about which groups constitute protected categories (see Appendix A; Garland & Chakraborti, 2012; Perry, 2010). These differences in hate crime definitions—and, in turn, in laws—have obvious implications for the reporting and recording of such crimes (Perry, 2010), which in turn result in sharply different levels of hate crime between countries. These differences complicate the attempt to conduct empirical, cross-national comparison.

In the context of Belgium, hate crime statistics are published in the "Politiële Criminaliteitsstatistieken 2000-2013" report (Belgian Federal Police, 2013). This report includes the category "racism and xenophobia" ("racisme en xenofobie"), which covers the number of criminal facts (acts, deeds, expressions, and intentions) that were registered by the Belgian Police Forces. These criminal facts comprise "violations of the Belgium law (July 30, 1981) that punishes the discrimination based on nationality, race, skin color, descent, or national or ethnic ancestry" of the victim (Belgian Federal Police, 2014, p. 1). Racism and xenophobia in Belgium, then, should be understood as criminal acts committed on the grounds of nationality, race, skin color, descent, or national or ethnic ancestry of the victim.

Similarly, Finland defines hate crimes as crimes committed against a person because of his or her specific characteristics—such as group membership, for example. Hate crime in Finland is defined as "crime against a person, group, somebody's property, institution, or a representative of these, motivated by prejudice or hostility towards the victim's real or perceived ethnic or national origin, religion or belief, sexual orientation, transgender identity or appearance, or disability" (Police College of Finland, 2014, p. 2). Finland does not provide a separate criminal code for "racist crime"; rather, racist crimes are considered a subcategory of hate crime and are recorded under the category racist crimes ("rasististen rikosten") in a series of police reports "Poliisin tietoon tullut viharikollisuus Suomessa" ("hate crimes reported to the police in Finland"), published by the Police College of Finland.

The language used to articulate the Swedish conceptualization of hate crime also invokes the idea that victims have certain characteristics that serve as the impetus for hate-motivated crimes. Racist and xenophobic crimes in Sweden are reported in the "Hatbrott" ("hate crimes") report under the category "xenophobic/racist hate crimes" ("främlingsfientliga/rasistiska hatbrott"). These are defined as "crimes committed because of fear, hostility or hatred towards a person, group, property or institution because of skin color, nationality or ethnic background that activates a reaction towards the person or those persons who is/are or is/are perceived to be of foreign or Swedish descent, or representatives of the people with Foreign or Swedish descent" (Swedish National Council for Crime Prevention, 2015, p. 50).

The Slovak penal code, meanwhile, defines hate crime as crimes with the "intent to publicly incite violence or hatred directed against a group of persons or an individual because of their belonging to a race, nation, nationality, skin color, ethnic group, origin, gender, or for their religion" (Criminal Code, Regulation no. 300/2005, see also Garland & Chakraborti, 2012). Race, then, constitutes a subcategory of hate crime. Racist crimes are published by the Ministry of the Interior of the Slovak Republic in the "Statistika kriminality versus slovensky republice" reports under the category "Crimes with a racial motive" ("Trestných činů s rasovým motívom").

As noted above, these differences in hate crime definitions have important implications for cross-national research for the very straightforward reason that they directly affect the data: given the differences outlined above, an offense that may be recorded and reported as hate crime in one country may not necessarily be deemed hate crime in another nation (Garland & Chakraborti, 2012). This renders direct cross-national comparison of hate crime levels difficult though not insurmountable, thanks to modern statistical methods.

Despite the data limitations outlined above, several European nations have developed relatively good systems for collecting information about hate crime in recent years (FRA, 2012a; Goodey, 2008). According to the FRA (2012a), Austria, Belgium, the Czech Republic, Denmark, France, Germany, Lithuania, Poland, and Slovakia have "good data" on hate crimes. Four additional countries—Finland, the Netherlands, Sweden, and the United Kingdom—have "comprehensive data," which by their definition means that the data include "a range of bias motivations, types of crimes and characteristics of incidents" (FRA, 2012a, p. 36). In most of these nations, the data on racially motivated crime have been collected since at least 2000 at the national and subnational levels, and with the exception of Denmark, Finland, and Sweden, there has been consistency in the methods used for reporting and recording (FRA, 2012a).

Although the amount of empirical research on hate crime is limited, the body of work on this topic is growing as the data improve. The data constraints outlined above mean that for the time being, research is largely confined to studies focusing on hate crime within a single nation—mainly Germany, the United States, and the United Kingdom. Within the United States, a sizable body of research has examined the jurisprudence of hate crime legislation (Greenspan & Levitt, 1993), hate crime offenses, and the characteristics of offenders (Messner, McHough, & Felson, 2004). A nascent line of research has also examined the role of the contextual factors in hate-motived violence (Disha, Cavendish, & King, 2011; Green et al., 1998). The most consistent finding of this body of work is that intergroup violence increases along with upsurges in out-group population. Research has also reported a significant and positive effect of crime rates on anti-Arab and Muslim hate crimes in the wake of 9/11 (Disha et al., 2011).

Studies in the United Kingdom, meanwhile, have focused mostly on issues of race and ethnicity (Bowling & Phillips, 2002). Racial riots and hate crime movements in this nation prompted an extensive body of work conducted on the relationship between "race" and the criminal justice system (Phillips & Brown, 1998), the perceptions and experiences of victims of racist crimes (Bowling, 1999), and the historical development of race relations in Great Britain (Hiro, 1992). Taken together, these studies revealed that racial and ethnic groups often became victims of bigoted crimes and that they were discriminated against by the police and within the criminal justice system. It has also been indicated that most of the offenders of racially motivated crime are young males (Aye Maung & Mirrlees-Black, 1994; see Bowling & Phillips, 2002).

The focus of Germany-based research on hate crime, meanwhile, has been placed on the contextual factors that allegedly relate to hate-motivated crime. A central argument examined in this body of work has been that the economic and social tensions that surrounded German unification led to social disruptions and consequently to increased levels of antiforeigner violence (Bleich, 2007; McLaren, 1999). The results of this body of work are congruent with findings in the United States and revealed a positive effect of the size or inflow of foreign-born population on levels of right-wing violence (McLaren, 1999). Krueger and Pischke (1997), meanwhile, found that the number of foreign-born residents in East Germany is positively related to the number of antiforeigner crimes, but this association did not hold true in West Germany.

A body of empirical work on hate crime is emerging in other European nations as well. Although this line of research is somewhat limited and largely descriptive at present, it nevertheless offers some valuable insights. Sweden-based research has, for example, examined the characteristics of offenders and the levels of bigoted crimes (Bunar, 2007; Roxell, 2011). One finding that emerges out of this research is that perpetrators are more commonly known than unknown to the victims and that the majority of offenders are males. It has also been indicated that the number of hate crimes has increased substantially over the 1997–2003 period (Bunar, 2007). Studies in Belgium, meanwhile, indicated that the residents of cities are less racist than those of villages where few foreigners reside (Schuermans & De Maesschalck, 2010).

For the most part, then, the extant research related to hate crime has focused on single nations. There are a few exceptions, however. Brustein and King (2004), for instance, examined the levels of anti-Semitic violence in pre-War Great Britain, France, Italy, Romania, and Germany over the 1899–1939 period. The authors found that levels of anti-Semitic violence were associated with a country's economic conditions, Jewish immigration, and—to some degree—with support for the political left. More recently, Dancygier (2010) examined hate-motivated violence in Western European nations and found that immigrant conflicts across different immigrant groups, cites, and countries are contingent on local economic conditions and immigrant electoral power. Using official data on racist and extreme crime in Western Europe, Koopmans (1996) also reported that increasing levels of racist and extremist violence are strongly correlated with influxes of refugees. The findings of these studies reaffirm the role of contextual factors in predicting hate crime in cross-national settings.

Taking all of these things into consideration, then, the general observation that can be made is that comparative work on hate crime remains limited, and the existing work focuses mainly on Germany, the United States, and the United Kingdom. There is also a scarcity of cross-national research on this topic, a fact that is due in part to data limitations (Goodey, 2008). The tide is beginning to turn, however. The reliability of nation- and region-specific data continues to improve, making it possible to conduct between-country trend analyses. The body of comparative work is therefore growing, and an analysis of patterns of hate crime across nations at the subnational level becomes an ever more achievable goal. That, then, is the goal of the current work: By utilizing improved data sources, we seek to make cross-national comparisons at the subnational level.

Theoretical Framework

The research on hate crime has been largely guided by intergroup theories on prejudice and bigoted violence. The major premise of these theories is that intergroup relations are shaped by intergroup competition over status, power, and material rewards (Blalock, 1967; Blumer, 1958). The argument that has generally been made is that dominant groups perceive gains on the part of minority groups as a threat to the existing social order: Because they fear that their privileged position is being eroded, they exhibit feelings of prejudice and discrimination toward subordinate groups. Within this theoretical framework, ethnic violence and prejudice are interpreted as arising out-of-group perceptions of threat and conflicts in group interests (Blalock, 1967; Blumer, 1958).

The argument has also been made that changes in the levels of intergroup conflict and prejudice vary depending on changes in the levels of perceived threat. This threat is typically measured by taking into account both the relevant economic conditions and the size of the minority population. According to group threat theory, as the minority group increases in size, the level of perceived threat increases and the dominant group becomes more fearful of losing its privileged position (Blalock, 1967). This is largely in accord with the defended neighborhood hypothesis, which suggests that the levels of hate crime are the greatest in places that experience a sudden inflow of out-group population members (Suttles, 1972).

A substantial body of work provides support for the theoretical frameworks outlined above. Green, Strolovitch, and Wong (1998), for instance, found that racially motivated crime occurred mostly in predominantly White New York city neighborhoods that experienced a minority influx over the 1987–1995 period, while McLaren (1999) reported that increases in foreign population were positively associated with right-wing violence in Germany between 1971 and 1995. Similarly, studies in the United Kingdom have revealed that racist violence is prevalent in areas with small but growing out-group population (see Bowling & Phillips, 2002). Using officially recorded data on racist crime, for example, Dancygier (2010) examined violence and hostility against Bangladeshi immigrations in the London Borough of Tower Hamlets. The findings revealed that racist crime was particularly prevalent in predominantly White areas that had experienced a sudden inflow of Bangladeshi immigrants. These findings support then the prediction that the relative size of the foreign-born population will have a positive effect on the levels of racially motivated crime rates across different regions and counties in the countries under investigation.

Interestingly, it has also been argued that the relative size of the foreign-born population may be negatively related to hate-motivated violence. According to the power-differential hypothesis, foreign-born persons are at a higher risk of victimization in areas where they constitute a smaller proportion of the total population, because in those places members of the dominant group may be less fearful of incurring negative consequence as a result of acting on their prejudice or committing hate crime (Levine & Campbell, 1972). Several studies provide support for this hypothesis (Disha et al., 2011). Maynard and Read (1997), for example, found the highest hate crime victimization rates in three provincial areas in the north of England, while Bowling (1999) showed that the risk of minority victimization is higher in local areas, where minorities comprise only a small proportion of the population than in towns and cities where they are better represented, proportionally. In non-UK settings, Disha, Cavendish, and King (2011) also found that the risk of victimization for Arabs or Muslims is highest in those U.S. counties, where the percentage of Arabs or Muslims is the lowest. By appealing to this framework, then, it is also plausible to expect that the relative size of the foreign-born population will be negatively related to racially motivated crime.

The threat framework also predicts a nonlinear effect of minority-group size on hate crime. This is because group size often relates to the ability to exert significant economic and political power. Thus, when a minority group grows large enough, it may curtail the efforts of the dominant group to commit hate crime (Levine & Campbell, 1972). There may be a tipping point, however, after which potential aggressors simply stop fearing the retribution for criminal acts. When this tipping point is reached, foreigners may become increased targets of hate-motivated crime. There are reasons, then, to predict that the foreign-born population size will be curvilinearly associated with the levels of racist crime. To test for possible nonlinear effects of foreign-born population size on racist crime, we incorporate a squared term for the foreign-born population into the analysis.

Group threat theory also suggests that intergroup violence will be positively influenced by economic scarcity. If economic resources are limited, members of majority groups may vent their frustration by committing violence against minority groups (Blalock, 1967). The link between economic conditions and bigoted violence is far from straightforward; however, while some studies do find an association between the incidence of hate crime and economic scarcity (Hovland & Sears, 1940), others fail to do so (Green et al., 1998; Krueger & Pischke, 1997). Meanwhile, in research focused on Chicago, Lyons (2007) reported that anti-Black hate crimes are more frequent in affluent, predominantly White neighborhoods—not places characterized by economic scarcity. This highlights the fact that the forces influencing hate crime are complex and may interact in complicated ways: The association between economic conditions and hate crime may at times be positive rather than negative, as group threat theory suggests, and we may even find null effects of economic conditions on racially motived crime if countervailing forces are at work.

Data and Method

To address the research questions at the heart of this work, we assembled three pooled, cross-sectional time series data sets comprised of different regions and counties across four European nations of interest. In our selection of European nations, we relied on the FRA classification of hate crime data collection systems in Europe (FRA, 2012a) and included those nations that "collect and publish sufficiently robust criminal justice data [on racist crime] to be able to do a trend analysis" (Goodey, 2008, p. 23). All four nations included in the sample utilized in this study have either good or comprehensive data collection systems on hate crime and publish officially recorded data on racist crime at the national and subnational levels (FRA, 2012a). These countries include Belgium, Finland, Slovakia, and Sweden.[1] The availability of data on hate crime at the subnational level determined the period of time under investigation (see Appendix A). Taken together, the data included in the sample encompasses approximately 17 years (1997–2013).

The data on hate crimes at the subnational level were taken from each country's official reports as indicated by the FRA (2013; see Appendix A). We selected the types of hate crime that were most frequently reported across all nations, namely racist or racist/xenophobic crimes. In Belgium and Sweden, racist crimes are recorded along with xenophobic crimes under the category racism and xenophobia (Belgium) and xenophobic/racist hate crimes (Sweden): Hence, the FRA (2013) reports them under the same category of racist crime.[2] Following the FRA's direction, we have included both racist and racist/xenophobic crimes under a single category. This measure is the outcome variable and has been recorded over time in each country under investigation. Hence, it is a measure of separate incidents that are categorized under the umbrella of the same variable (racially motivated crime) for the same set of subnational units in the period of time under examination.

It should be noted that the measure of hate crime used in this study serves as a proxy for the actual rate of crime (FRA, 2012a). The FRA cautions that hate crime rates may fluctuate from year to year as a result of "how racist crime is defined in criminal law, changes in how (the characteristics of) incidents of racist crime are recorded, the willingness of victims and/or witnesses to report incidents, the actual occurrence of racist crime" (FRA, 2012a, p. 160). Following the FRA's 2012a report, two countries, Sweden and Finland, reported changes in data collection systems in 2008 (FRA, 2012a, p. 161). To control for this change, we incorporated a dummy variable into the analysis.

As noted above, this study utilizes three different geographical divisions as the unit of analysis. The selection of these divisions is based on the European Union's classification system. Referred to as NUTS (nomenclature of territorial units for statistics), this system was developed by the EU to enable and support socioeconomic analyses of regions (Eurostat, 2011). The NUTS system divides countries into subnational jurisdictions according to both population size and economic, political, and cultural factors (Eurostat, 2011) and been widely utilized in prior research (see, e.g., Jesuit & Mahler, 2004). The NUTS geocode standards refer to administrative subdivisions within countries and are broken down into three levels (NUTS 1, NUTS 2, and NUTS 3), and the data sets in the current analysis reflect this threefold division. The first data set centers on major European regions

(NUTS 1) as the unit of analysis, whereas the second utilizes basic European regions (NUTS 2), and the third uses European subdivisions at the county level (NUTS 3). While there are specific thresholds adopted for population size for each NUTS level (NUTS 1: between 3 million and 7 million; NUTS 2: between 800,000 and 3 million; NUTS 3: between 150,000 and 800,000), the areas of the regions at different NUTS levels diverge considerably (Eurostat, 2011).

The availability of hate crime data at the subnational level also informed this threefold division as well as determining the selection of nations investigated herein. To our knowledge, among the European nations, only Belgium, Finland, Slovakia, and Sweden provide data on racially motivated crime at all three NUTS levels. Given that, only these four nations were included in the current research. All nations included in the sample collected data on hate crime at the NUTS 3 level, corresponding to a total of 90 counties (917 county-years; see appendix A). Although data on hate crime in Belgium are also published at the NUTS 2 level, data on hate crime at this level in the remaining three nations have been aggregated from the smaller NUTS 3 units.[3] The NUTS 2 data set therefore contains a total of 27 regions which generates 278 region-years for the analysis. Finally, the NUTS 1 level is calculated by summing the counts of racist crime from the smaller NUTS 2 units. A total of 8 major regions are included in the NUTS 1 data set, which gives 86 region-years for the analysis.

The present study includes several indicators of structural conditions that are hypothesized to be associated with the levels of racist or racist/xenophobic crime at the subnational level. To assess economic conditions, the regional gross domestic product (GDP) per capita (calculated in constant dollars) and regional unemployment rates (measured as a percentage of the total labor force) were obtained from the Eurostat Database. The GDP measure was available at all geographical levels used in this study, whereas data on unemployment rates were accessible only at the NUTS 1 and NUTS 2 levels. To rectify this shortcoming, we obtained the unemployment rates at the NUTS 3 level from the OECD regional database.[4] The data on unemployment rates in Belgium at the NUTS 3 level were taken from the Belgium National Employment Office.

To assess the size of out-group population members, this study incorporated the number of people making up the foreign-born population in a given year as reported by the National Statistical offices.[5] Because the Statistical Office of the Slovak Republic does not provide data on the foreign-born population, what is included instead is the number of persons with a permanent residence permit in a given year as reported by the Ministry of the Interior of the Slovak Republic.

This study also incorporated several control variables used in previous research on intergroup crime (Disha et al., 2011). These variables are population density, the percentage of population 15–24 years of age, and the total number of crimes (expressed as a rate per 100,000 population). Data on the first two measures were taken from the Eurostat Database and from the National Statistical offices, respectively. Data on the total number of crimes at the subnational levels in Finland were obtained from the National Statistical office—Statistics Finland, whereas those in Belgium were obtained from the country's Federal Police. The data on total number of crimes in Sweden were taken from the National Council for Crime Prevention, and, in the Slovak Republic, from the Ministry of the Interior of the Slovak Republic. Data on the control variables were available at all NUTS levels.

The data utilized in this study are structured as pooled, cross-regional/county annual time series. To address our research questions, we estimated a panel count model with the offset of logged population, where time is the first level of the data structure (Level 1) and is nested within the region/county (Level 2; Rabe-Hesketh & Skrondal, 2008). This technique allows estimating a panel count model of racist or racist/xenophobic crime as a function of time and the structural correlates of racist or racist/xenophobic crime in each region/county under investigation. Thus, by employing a multilevel model, we refrain from a direct comparison of hate crime levels and instead examine the changing patterns of racist crime at the subnational level across different European countries. This model at Level 1 then can be expressed as follows:

$$\mu_{ij} = \mathrm{E}(\mathrm{Y}_{0j}|\mathrm{TIME}_{ij}\ \varepsilon_{ij}) = \exp(\pi_{0j} + \pi_{1j}\ \mathrm{TIME}_{ij} + \varepsilon_{ij}),$$

where $\varepsilon_{ij}|\mathrm{TIME}_{ij} \sim N(0, \psi_{1i})$ and the ε_{ij} are independent across regions j.

The model at Level 2 was expressed as:

$$\pi_{0j} = \beta_{00} + \upsilon_{0j}$$
$$\pi_{1j} = \beta_{10} + \upsilon_{1j}$$

where $\upsilon_{0j} \sim N(0, \psi)$,

where, μ_{ij} refers to the racially motivated crime for the ith unit at the Level 1 and the jth unit at the Level 2. Y_{ij} has a Poisson distribution with exposure TIME_{ij} and random error ε_{ij}. At Level 1, π_{0j} is the intercept for the unit j, ε_{ij} is the stochastic error, and π_{1j} is the coefficient for the effect time in the subnational unit j. At Level 2, υ_{0j} and υ_{1j} are random effects that account for random variation at Level 2, while β_{00} and β_{10} are the random effects for the intercept and the TIME slope, respectively.

Issues of autocorrelation and nonstationarity are critical to address with dealing with panel data because they may lead to biased results. With regard to nonstationarity, the results of a Dickey-Fuller test for unit root revealed that nonstationarity is not an issue for the current analysis. The null hypothesis of the nonstationary-dependent variable—racially motivated crimes—was rejected at the .001 level in all three data sets. The Wooldridge test for autocorrelation in panel data, however, detected significant autocorrelation at all three NUTS levels. Given this finding, models at all NUTS levels include the first-order autoregressive term in an attempt to control for within-unit autocorrelation. Heteroscedasticity was also detected at all NUTS levels, and so the models additionally include Huber-White robust estimates of standard errors. In all models, time is controlled by including both time trend and country-specific trends. Finally, to control for the contextual effects related to national context, country-specific dummy variables were included. These country-specific dummies control for unknown and/or unmeasured country characteristics that are constant over time. Thus, they allow levels of hate crime to differ between countries.

The panel rate models employed here utilize a hybrid approach, which uses within-unit variance to achieve strong causal inference. This approach is especially suitable for the current research because of the considerable differences in hate crime definitions cross nationally. Following Allison (2005), we decomposed each time-varying predictor into a unit-specific mean and a deviation from that mean. For simplicity, the results displayed below represent only differences from group-centered means. Because the dependent variable, racially motivated crimes, is positively skewed with some zero counts, it is modeled as a count outcome using a Poisson sampling distribution. The conditional distribution of this variable is thus specified via a link log function (Rabe-Hesketh & Skrondal, 2008). Analyses were conducted in SAS Version 9.3, using the glimmix procedure.

Results

Table 1 displays descriptive statistics of the variables used in this study at all three NUTS levels. Of note here is that the racially motivated crimes referred to in the three data sets are recorded as counts. We converted these counts into racist crime rates through an "offset" function in the panel count models to account for the number of opportunities associated with each event per subnational unit. Specifically, we used the offset of the logged population with coefficient constrained to 1 to adjust for differences in population sizes across subnational units. The measure of racially motivated crime, then, should be understood as racist crime rates rather than counts. To provide additional information on this measure, Table 1 also presents the descriptive statistics for racially motivated crime converted into rates (per 100,000).

Statistics in Table 1 show that the mean of racially motivated crime rates is 17.55 with a standard deviation of 13.13 at the NUTS 1 level, 14.24 with a standard deviation of 12.74 at the NUTS 2 level,

Table 1. Descriptive Statistics Used in the Analysis

Variables	NUTS 1				NUTS 2				NUTS 3			
	Mean	*SD*	Min	Max	Mean	*SD*	Min	Max	Mean	*SD*	Min	Max
Dependent variable												
Racially motivated crime count	547.56	441.58	33	2,174	167.51	211.87	3	1,382	51.07	119.37	0	1,382
Racially motivated crime rate (per 100,000)	17.55	13.13	.69	61.64	14.24	12.74	.22	69.75	12.21	11.87	0	69.75
Independent variables												
Foreign born (%)	10.15	8.25	.32	31.48	7.51	6.29	.26	31.48	5.92	5.08	0.22	31.48
GDP/per capita	30,386.1	13,744.4	4,100	62,000	26,550.7	11,634.4	3,100	62,000	24,331.4	9,257.6	2,500	62,000
Unemployment rate	9.48	4.30	3.50	19.40	8.62	4.62	1.9	25.0	11.11	5.60	3.24	27.7
Control variables												
Total crime rate (per 100,000)	10,582.8	4,771.9	1,699.1	1,7564.5	9,061.4	4,356.7	1,245.3	20,071.1	8,463.8	3,546.9	1,133.9	20,071.1
Population 15–24 (%)	12.86	1.28	11.47	17.07	12.95	1.41	10.60	17.46	12.72	1.31	10.60	17.78
Population density (per km2)	932.1	2,102.4	5.9	7,131.1	437.3	1,220.1	3.3	7,131.1	281.5	708.8	2.0	7,131.1
Variable used as the offset												
Total population	3,822,561	1,687,365	959,318	6,325,740	1,119,702	484,914	246,820	2,091,473	344,904	338,972	40,574	2,091,473

Note. GDP = gross domestic product; NUTS = nomenclature of territorial units for statistics.

and 12.21 with a standard deviation of 11.87 at the NUTS 3 level. These results demonstrate a great deal of variation between subnational units with regard to the levels of racially motivated crime at all three levels. These findings are also largely in accord with the extant body of work on hate crime, which indicates divergence among hate crime levels across nations (Goodey, 2008; Perry, 2010). Recall that what is categorized as a hate crime in one country may not be categorized as such in another. Other scholars have noted this fact, pointing out that various conceptual, legislative, and methodological approaches to hate crime in different nations may factor significantly into hate crime reporting (Perry, 2010). The results in Table 1 thus furnish further evidence for this claim.

The bivariate analysis revealed that GDP (per capita) was highly correlated with three variables: total crime rate at all three NUTS levels, the size of the foreign-born population at the NUTS 1 and NUTS 2 levels, and population density at the NUTS 1 level. Given this collinearity, we applied a log transformation to GDP. Notably, though, the effect of GDP on the dependent variable remained unchanged in the model (whether or not they have been transformed in subsequent models).

Table 2 presents the results of racially motivated crime regressed on structural covariates at the NUTS 1, NUTS 2, and NUTS 3 levels in the four nations under the investigation. Models 1, 4, and 7 are fully unconditional and show the observed variability in racially motivated crime between the subnational units and the estimated mean level of racially motivated crime across the subnational units at the NUTS 1, NUTS 2, and NUTS 3 levels, respectively. Of note here is that the sample of four nations under investigation yielded a relatively small number of cases at the NUTS 1 level. This in turn resulted in limited degrees of freedom in the fixed-effects modeling utilized in this study. Given that, only three structural covariates were incorporated into the equations at the NUTS 1 level (see also Table 3).

Models 2, 3, 5, and 8 add structural covariates that are hypothesized to be associated with racially motivated crime. The results in all four of these models indicate that the relative size of the foreign-born population is significantly related to racially motivated crime at all three NUTS levels. The coefficients for the regression equations are significant and negative at the NUTS 1 ($b = -.289$, $p < .01$—Model 2; $b = -.301$, $p < .01$—Model 3), NUTS 2 ($b = -.298$, $p < .001$—Model 5), and NUTS 3 ($b = -.106$, $p < .05$—Model 8) levels. In other words, a bigger share of the foreign-born population in society produces lower levels of racially motivated crime. This is consistent with the power-differential hypothesis, which suggests that hate crime is more likely to occur in the areas where a minority population comprises a relatively small proportion of the total population (Green et al., 1998; Levine & Campbell, 1972).

Models 2, 3, and 5 also reveal that the relationship between the foreign-born population size and racially motivated crime is concave curvilinear. With the exception of Model 8, the regression coefficients for the foreign-born population squared are significant and positive in sign (NUTS 1 $b = .034$, $p < .05$—Model 2; NUTS 1 $b = .037$, $p < .05$—Model 3; NUTS 2 $b = .033$, $p < .01$—Model 5). This finding indicates that the relative size of the foreign-born population exerts some buffering effects, in a sense that up to a point it provides a measure of protection. When the tipping point is reached, however, hate-motivated violence against foreigners can instead rise together with foreign-born population growth.

Comparing the variance components from Models 2, 3, 5, and 8 to those obtained in Models 1, 4, and 7, respectively, reveals that approximately 54% (.54 = [.100–.046]/.100) and 56% (.56 = [.100–.044]/.100) of subnational unit-level variance at the NUTS 1 level, 39% (.39 = [.092–.056]/.092) at the NUTS 2 level, and 24% (.24 = [.116–.088]/.116) at the NUTS 3 level are accounted for by the independent variables included in these models.

Models 6 and 9 add the control variables into the models. Notably, adding these variables yielded no significant change to the foreign-born population size relative to the previous Models 5 and 8. The coefficients for the regression equations are significant and negative in sign at both NUTS 2 ($b = -.300$, $p < .001$—Model 6) and NUTS 3 ($b = -.122$, $p < .01$—Model 9) levels.

Table 2. Hybrid Panel Rate Model Regressing Racially Motivated Crime on Structural Covariates.

	NUTS 1			NUTS 2			NUTS 3		
Independent Variables	Model 1 ($n = 86$)	Model 2 ($n = 86$)	Model 3 ($n = 86$)	Model 4 ($n = 278$)	Model 5 ($n = 278$)	Model 6 ($n = 278$)	Model 7 ($n = 917$)	Model 8 ($n = 917$)	Model 9 ($n = 917$)
Fixed effects									
Constant	−9.26*** (.428)	−4.04 (3.94)	−10.68* (.186)	−10.02*** (.430)	−21.17*** (4.98)	−18.27*** (4.02)	−9.98*** (.092)	−17.04*** (2.48)	−15.23** (2.60)
Foreign born (%)		−.289** (.092)	−.301** (.099)		−.298*** (.066)	−.300*** (.046)		−.106* (.044)	−.122** (.040)
Foreign-born (%) squared		.034* (.014)	.037* (.016)		.033** (.011)	.045*** (.013)		.048 (.091)	.022* (.010)
GDP/per capita (ln)		−.155 (.260)	–		−.277 (.297)	−.051 (.272)		.095 (.250)	.255 (.247)
Unemployment rate			−.020 (.024)		−.024 (.016)	−.014 (.015)		−.006 (.136)	−.009 (.014)
Total crime rate (per 100,000)						.061** (.022)			.030 (.023)
Population 15–24 (%)						.260*** (.038)			.262*** (.048)
Population density (per km^2)						−.055** (.020)			−.065*** (.015)
Random effects									
Variance	.100* (.044)	.046* (.022)	.044* (.020)	.092*** (.017)	.056*** (.011)	.038*** (.007)	.116*** (.012)	.088*** (.008)	.082*** (.008)
1st Order Autocorrelation	.864*** (.063)	.706*** (.150)	.693*** (.145)	.831*** (.036)	.736*** (.064)	.644*** (.085)	.676*** (.044)	.550*** (.055)	.533*** (.058)
Log likelihood	−8.92	6.06	16.85	76.66	83.56	121.88	1,077.96	1,073.21	1,122.46
Generalized χ^2/df	1.09	1.09	1.08	1.11	1.12	1.13	1.03	1.02	1.03

Note. All models include nation fixed effects, time trend, and country-specific time trends. The estimates represent difference from group-centered mean. Standard errors are in parentheses.
*p < .05. **p < .01. ***p < .001.

Table 3. Hybrid Panel Rate Model Regressing Racially Motivated Crime on Structural Covariates—NUTS 1.

	NUTS 1		
Independent Variables	Model 1 ($N = 86$)	Model 2 ($N = 86$)	Model 3 ($N = 86$)
Fixed effects			
Constant	−10.72* (.377)	−12.12 (2.08)	−10.46* (.797)
Foreign born (%)	−0.304** (.090)	−0.213** (.073)	−.399*** (.059)
Foreign born^2 (%)	0.037** (.013)	0.024* (.011)	0.070*** (.013)
Total crime rate (per 100,000)	0.044 (.042)	-	-
Population 15–24 (%)		0.390*** (.107)	-
Population density (per km^2)			−0.084*** (.017)
Random effects			
Variance	0.044* (.021)	0.035** (.015)	0.041* (.020)
1st Order Autocorrelation	0.697*** (.150)	0.647*** (.161)	0.693*** (.153)
Log likelihood	39.94	3.62	31.36
Generalized χ^2/df	1.09	1.10	1.10

Note. All models include nation fixed effects, time trend, and country-specific time trends. The estimates represent difference from group-centered mean. Standard errors are in parentheses.
*p < .05. **p < .01. ***p < .001.

The models also report that the regression coefficients for the squared terms for the foreign population size are significant and positive (NUTS 2 $b = .045$, $p < .001$—Model 6; NUTS 3 $b = .022$, $p < .05$—Model 9), which again is indicative of concave curvilinear relationship between racially motivated crime and foreign-born population size at both levels.

The results in Models 6 and 9 also reveal a significant and positive effect of the percentage of the young population between 15 and 24 on racially motivated crime at the NUTS 2 and NUTS 3 levels, respectively. All else equal, as the percentage of young population increases, the occurrence of racially motivated crime is likely to increase as well. This is largely in concert with previous findings from a fairly large body of work on hate crime, which has indicated that most of the offenders of hate-motivated crime were young adults (Aye Maung & Mirrlees-Black, 1994; Disha et al., 2011; see Bowling & Phillips, 2002). The present study confirms that this body of work has some merit and further demonstrates that the share of the young population in the total population indeed positively influences the levels of racially motivated crime across different geographical units.

Model 6 also reports a significant effect of the total crime rate on racially motivated crime (Bunar, 2007; Disha et al., 2011). Consistent with previous research on hate crime (Disha et al., 2011), the regression coefficient for this variable is significant and positive at the NUTS 2 level ($b = .061$, $p < .01$). The effect of this variable on racist crime does not hold true at the NUTS 1 and NUTS 2 levels, however. Additional analyses (not presented here) revealed that the total crime rate is significantly associated with racially motivated crime at these two levels but without other independent variables included in the model. This suggests that a positive association between the total crime rate and racially motivated crime is accounted for the other variables included in the model. While future investigations will help shed additional light on this issue, one possibility is that the impact of this variable on racist crime is contingent on the geographical unit of analysis that is employed.

Finally, the results in Models 6 and 9 reveal that population density is significantly associated with racially motivated crime, holding all other variables constant. In both models, the coefficients for regression equation are negative in sign in both models (NUTS 2 $b = -.055$, $p < .01$—Model 6; NUTS 3 $b = -.065$, $p < .001$—Model 9). In other words, hate-motivated crimes occur more frequently in less populated areas, after adjusting for the size of the population. Maynard and Read

(1997) found the highest hate crime victimization rates in three provincial areas in the north of England, while Schuermans and De Maesschalck (2010) reported that the residents of cities are less racist than those of villages where few foreigners reside. Some research has also shown that the risk of minority victimization is higher in *local* areas, where minorities comprise only a small proportion than in the more cosmopolitan areas of towns and cities (Bowling, 1999; Smith, 1989). The finding of negative effect of population density is in line with this body of work and further demonstrates that the population density negatively influences the levels of racially motivated crime across different geographical units in comparative settings.

Comparing the variance components from Models 6 and 9 to those obtained in Models 5 and 8, respectively, the results reveal that approximately 32% (.32 = [.056–.038]/.056) of subnational unit-level variance at the NUTS 2 level and 7 % (.07 = [.088–.082]/.088) at the NUTS 3 level are accounted for by the control variables included in these models.

The results of racially motivated crime regressed on the remaining structural covariates at the NUTS 1 level are reported in Table 3. Given the limited degrees of freedom mentioned above, only one control variable is included in the model along with the independent variables found to be consistently related to racially motivated crime across all three NUTS levels, namely, the relative size of the foreign-born population and the relative size of the foreign-born population squared (see Table 2).

The findings in Table 3 are largely consistent with the analysis presented above. The regression coefficients for the relative size of the foreign-born population ($b = -.304$, $p < .01$—Model 1; $b = -.213$, $p < .01$—Model 2; $b = -.399$, $p < .001$—Model 3) and the relative size of the foreign-born population squared ($b = .037$, $p < .01$—Model 1; $b = .024$, $p < .05$—Model 2; $b = .070$, $p < .001$—Model 3) are significant across all the models, indicating a concave curvilinear relationship between the foreign-born population size and racially motivated crime. Also similar to the aforementioned results, Models 2 and 3 reveal a significant and positive effect of the percentage of young population and a significant and negative effect of population density on racially motivated crime, respectively. We also find the regression coefficient for the total crime rate to be nonsignificant at the NUTS 1 level, which is similar to the results at the NUTS 3 level. This again suggests that the association between hate crime and the total crime rate may be sensitive to, or differ along with, the unit of analysis that is employed.

Discussion and Conclusion

In the present study, we have examined the effects of subnational correlates on the levels of racially motivated crime across different regions over time in Belgium, Finland, Slovakia, and Sweden. Drawing upon group threat theory (Blalock, 1967), we have hypothesized that the relative size of foreign-born population will be positively associated with racially motivated crime. Alternatively, the power-differential hypothesis suggests that the relative size of the foreign-born population will be negatively associated with racially motived crime (Levine & Campbell, 1972). Recall, too, that prior work has yielded mixed findings with regard to the effects of economic conditions on hate crime, so while we anticipated an association between levels of racist crime and economic scarcity, we posited that the association found may be either positive or negative.

In line with our expectations, we find that the relative size of the foreign-born population is negatively related to racially motivated crime at three NUTS levels. This is congruent with the power-differential hypothesis, which suggests that hate crime is more likely to occur in areas, where a minority population comprises a relatively small proportion of the total population. The argument here is that, as the size of the minority population increases, their potential power and the possibility for retaliation increases in tandem. As this happens, the majority group becomes more fearful of committing crime motivated by bias (Levine & Campbell, 1972). The findings presented above indicate that this argument has some merit.

The analyses presented in this study also yield some interesting findings with respect to the control variables. We find that racially motivated crime is positively related to the total crime rate at the NUTS 2 level and the percentage of young population across all the models. Notably, the positive effect of the number of total crime does not hold true at the NUTS 1 and NUTS 3 levels, which suggests that the impact of this measure on racist crime is sensitive to the unit of analysis employed. Also in line with prior work (Schuermans & De Maesschalck, 2010), we find a significant and negative effect of population density on racist crime. This suggests that racist crimes are more prevalent in less populated places. Taken together, the analyses presented here reaffirm the findings from the extant body of work on hate crime (Bunar, 2007; Disha et al., 2011; see Bowling & Phillips, 2002).

The results also reveal that the relationship between the foreign-born population size and racially motivated crime is concave curvilinear. That is to say, the foreign-born population group is at a very high risk of hate crime victimization when it constitutes a relatively small proportion of the total population. Thus, there is an inverse relationship between minority-group size and hate crime risk, providing a modicum of support for the power-differential hypothesis, which expects decreases in racist crimes as the foreign-born population size increases (Green et al., 1998; Levine & Campbell, 1972). However, there may be a tipping point, or a flash point, after which this trend is altered and the relationship changes. When the minority population increases past a certain point, such that it constitutes an extremely large proportion of the society, risk of victimization may increase once again. Consider a hypothetical situation wherein a country experiences a sudden, substantial inflow of foreigners. In such cases, if the size of the foreign-born population increases to a point where they are perceived to represent a threat (or a potential threat) to the existing power and economic structures, members of this population may become more of a target. This is exactly the type of scenario that we consider a possible explanation for the U-shaped trend relating the relative size of the foreign-born population to racially motivated crime found in our data.

Another plausible explanation for the concave curvilinear relationship between the foreign-born population size and racist crime found herein may be related to nation-specific contexts. Notably, in contrast with some other Western nations, Finland, Sweden, and Slovakia did not experience long and extensive inflows of minorities from postcolonial countries. Furthermore, while these three nations have relatively small non-White population percentages (Virtanen, 2000; Von Hofer, Sarnecki, & Tham, 1997), there has been a substantial increase in recent years with respect to the number of foreigners represented in country. This is true for all three nations. Immigration to Belgium, moreover, is unique in some aspects: As Hebberecht points out (1997), “immigration to Belgium differs from that in other European countries; it is not related to its colonial and post-colonial history in the former Belgian Congo” (p. 152). In fact, “Belgium has the smallest post-colonial immigration of all former colonial empires. Only since the 1990s has it allowed greater numbers of Congolese within its borders” (Goddeeris, 2015, p. 434). Specifically, the fact that Finland, Slovakia, and Sweden only recently experienced a sudden, substantial inflow of minority group members means that the increasing share of foreign-born population may be particularly likely to be perceived as a threat. If so, they may be particularly likely to become victims of hate-motivated violence. Similarly, while Belgium has experienced an inflow of the Maghrebis and Turks since the 1960s (Hebberecht, 1997), an additional substantial influx of Congolese in recent years could contribute to increases in hate-motivated violence.

Although the exact mechanisms through which immigration and foreign-born population size influence hate crime remain unclear, the results of the analyses offered here are largely consistent with Ferraro’s (2013) findings. In that work, Ferraro examined the effects of structural correlates on anti-immigrant hate crime in the UnitedStates. He finds conflicting results, however: While traditional immigrant-receiving communities offer sources of support and organization to their members, which may lower hate crime rates, new destinations experience increased hate crime rates. This may reflect increased levels of perceived threat, but—as noted by Ferraro himself—more study is needed to in the future to "clarify these dual findings" (p. 195).

Although the present work does not offer a complete response to Ferraro's call for additional study, it does further suggest that complex processes with respect to demographics may be at play. It raises the possibility that a long-term influx of foreigners in certain European nations reduces the levels of hate crime therein by providing buffering effects. In other words, it may be that over the long term, the presence of foreigners within a society influenced social conditions in a manner that provided protection for immigrant groups, in turn leading to decreased levels of hate crime. On the other hand, recent influxes of foreign-born population members may increase hate-motivated violence by increasing levels of perceived threat. Furthermore, the inflow of foreigners could be perceived as more sudden in Slovakia, Sweden, and Finland than elsewhere, given that the share of foreigners has increased substantially in those countries only in recent years (Virtanen, 2000; Von Hofer et al., 1997). If so, this would lend support for the defended neighborhood hypothesis, which posits that a rapid influx of out-group population is a crucial determinant of elevated levels of bigoted violence (Green et al., 1998).

Although we can only speculate, it seems likely that adequate explanations for any link between the relative size of the foreign-born population and hate crime goes beyond traditional formulations of the group threat theory. Instead, it involves more complicated scenarios about the effects of population composition on hate crime. While future studies may shed additional light on this issue, the implication is that the curvilinear impact of the relative size of the foreign-born population on racist crime may be related to the societal contexts.

The current research expands the existing body of work on hate crime and addresses spatio-temporal limitations by incorporating data from four nations over time. By doing so, this study is one of the first to address critical gaps in the literature on hate crime. This is an important contribution, but much work remains to be done. One important caveat pertains to the use of the relative size of the foreign-born population as a proxy for hypothesized threat. The term "foreign born" identifies persons who were born outside the country in which they reside, thus, the relative size of the foreign-born population utilized in this study represents the percentage of people born outside the countries under investigation, as reported by the National Statistical offices. This includes both White and non-White population as well as both European/non-European populations.

It is important to note, however, that group threat theory has traditionally been formulated with reference not just to categories of race in general but to the Black–White dichotomy in particular. In this strain of scholarship, group threat theory has been particularly utilized as a means of interpreting reactions to inflows of African Americans to areas that had previously been predominantly White (Blumer, 1958; King & Wheelock, 2007). Thus, this theory adopted group-specific measurement of independent and dependent variables, wherein hate crimes and prejudice against certain group were assumed to be influenced by the relative size of that group. Only recently has this model been extended to include foreigners in an attempt to explain rising levels of anti-immigrant sentiment (Ferraro, 2013; see, e.g., Quillian, 1995).

The porosity of the data for subnational jurisdictions across all the nations under investigation effectively precluded insertion of the group-specific measurement of independent and dependent variables.[6] Nonetheless, incorporating the relative size of group-specific minorities as a predictor variable—and minority-motived hate crimes as a separate category—is worthy of serious attention in future research. This is particularly true because there are limitations inherent in using the relative size of the foreign-born population as a homogenous category: Foreign-born populations differ in terms of country of origin, duration of residence, access to economic and political resources, immigrant background, social capital, and so forth, and these differences may have important implications for the risk of hate crime victimization.

With this in mind, inclusion of group-specific measurement of independent and dependent variables would be very instructive. We know, for instance, that certain minorities in certain countries are particularly vulnerable to being victims of hate-motivated violence. For example, in 2010, a substantial share of hate crimes committed in Sweden were motivated by sexual orientation—or, better said, by bias against certain sexual orientations—while in France, it was anti-Semitism that appeared to underlie a large number of hate crimes (FRA, 2012b).[7] Additionally, there are substantial differences among the minorities in each nation under investigation not only in terms of their socioeconomic and demographic backgrounds but also in terms of their relationships with the dominant groups. These differences may have important implications for their risk of hate crime victimization. As data on hate crime continue to improve, future research may seek to extend the current research by examining the effect of the relative size of the specific minorities on group-specific crimes motivated by bias.

Data constraints mean that we were unable in the present study to differentiate between hate crimes committed by the natives and those committed by minorities. Consequently, it is plausible that the data utilized herein encompassed incidents of majority–minority, minority–majority, or minority–minority attacks. Successfully determining the precise relationship of victim and offender will ultimately yield more reliable data on hate crime victimization in the nations under investigation.

As noted earlier, the availability of data on hate crime at the subnational level informed the threefold division (NUTS 1, NUTS 2, and NUTS 3) used in this study as well as the sample of nations included. Thus, the countries included in this study were not a random sample. This study utilized the best data sources available at the three NUTS levels, but if it is possible to include a larger sample of nations in future research, then the generalizability of the findings will be improved. Gaining access to reliable data from additional countries—perhaps nations outside the EU or those with markedly different political or socioeconomic histories or systems—would also be valuable, for it will enable additional investigation into the complex array of factors that may be relevant when trying to understand the phenomenon of hate crime.

Future research may also incorporate other predictors found to be related to hate crime. Research indicates, for example, that education level may be important in predicting crime motivated by bias. This line of work shows that hate crime offenders tend to have lower levels of education (Gadd & Dixon, 2009; Willems, 1995). Given limitations on the data, we incorporated only several structural covariates, but improvements in data collection will allow future studies to include additional variables such as education level.

Another potentially fruitful avenue for future research might be exploration of the levels of hate crime at colleges in the nations under investigation. Indeed, research shows that hate crimes are reported less frequently on those college campuses that have larger numbers of Black and Latino students (Stotzer & Hossellman, 2012). Interestingly, this negative association between hate crime reporting and college hate crime is to some extent congruent with the present study: Indeed, we find that until a certain threshold is met, minority groups are at the highest risk of victimization in places where they constitute a small proportion of the total population. We may therefore speculate that minority population size will have an effect on hate crime at colleges in the nations assessed in the current research. Our focus has been on the incidence of racist crime in the larger society, but more focused study may become feasible as data on hate crime at European colleges become increasingly available.

In closing, the findings from the current study have important implications regarding future research related to hate-motivated violence. At a time when more and more scholars, practitioners, and policy makers on both sides of the Atlantic are concerned about issues related to hate crime, this study sheds light on some of the factors that must be taken into account in the attempt to predict and understand this type of crime.

Appendix A

Country	Source	Definition	Period Covered	Number of Units		
				NUTS 1	NUTS 2	NUTS 3
Belgium	Data collected by Federal Police, published in the “Politiële Criminaliteitsstatistieken 2000–2013”	Racism and xenophobia (“Racisme en xenofobie”)	2000–2012	3	11	43
Finland	Data published by Police College of Finland in a series of annual reports on hate crimes (“Poliisin tietoon tullut viharikollisuus Suomessa”)	Racist crime (“Rasististen rikosten”)	1999–2012	1	4	18
Slovakia	Data published by the Ministry of the Interior in monthly report on crime statistics (“Statistika kriminality v. slovensky republice”)	Crime with a racial motive (“Trestných činů s rasovým motívom”)	1997–2013	1	4	8
Sweden	Data published by the Swedish National Council for Crime Prevention in annual reports on statistics relating to offences with an identified hate crime motive (“Hatbrott. Statistik över polisanmälningar med identifierade hatbrottsmotiv och självrapporterad utsatthet för hatbrott”)	Xenophobic/racist hate crime (“Främlingsfientliga/ Rasistiska Hatbrott”)	1999–2012	3	8	21

Note. Definitions and Sources of Data on Racist Crimes in the Nations under Investigation (based on FRA, 2012 and FRA, 2013). NUTS = nomenclature of territorial units for statistics.

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Notes

1. Goodey (2008) does not include Belgium in his classification of countries with robust data on racist crime though he classifies Belgium as having “good” systems in place” (p. 21). Consequently, for this study, appropriate Belgian authorities were contacted to evaluate their consistency in recording hate crime. According to the Federal Police in Belgium, there have been no changes in policy or the judicial

nomenclature with respect to racist and xenophobic crimes recorded in the period under investigation (document available upon request).

2. According to the Federal Police in Belgium, racist crimes are recorded along with xenophobic crimes, and "as a consequence, it is not possible to make the distinction between racism and xenophobia in the "Police Crime Statistics" (Belgian Federal Police, 2015). Similarly, according to the National Council for Crime Prevention in Sweden, racism and xenophobia are "often used as synonyms" (Swedish National Council for Crime Prevention, 2015). Racist or xenophobic crimes are thus recorded once under the same category, namely "racism and xenophobia" in Belgium and "xenophobic/racist hate crimes" in Sweden. This excludes the possibility that racist crimes are recorded twice or double counted. Rather, each incident is counted only once and recorded under a single merged category of "racist/xenophobic" crime. As such, racism and xenophobia cannot be considered as mutually exclusive nor can they be disentangled at the present time.
3. In Sweden and Slovakia, the data on hate crime were collected only at the national and lower level administrative divisions (NUTS 3). Thus, we aggregated the number of racist crimes in these countries to their corresponding basic regions by adding counts of racist crime from smaller units to a larger unit (NUTS 2). In Finland, the data on racist crime are recorded at the city level. Although these data are not collected from the entire regions, they may be considered as indicative of the levels of hate crime for these regions, so we aggregated the number of racist crimes from Finland's cities to corresponding basic regions (NUTS 2).
4. The data on unemployment rates from Eurostat and OECD at NUTS 1 and NUTS 2 levels showed high correlation ($r = .93$ at NUTS 1 level and $r = .95$ at NUTS 2 level).
5. These offices are the Directorate—General Statistics Belgium, Statistics Finland, the Statistical Office of the Slovak Republic, and Statistics Sweden (see Eurostat website http://ec.europa.eu/eurostat/c/portal/layout?p_l_id=119314&p_v_l_s_g_id=0 for more detailed information).
6. Given that the nations under investigation do not offer information on the relative size of minority groups at the subnational level, we used the relative size of the foreign-born population to gauge the hypothesized threat. The concept of foreigners, however, should not be equated with the notion of minorities. According to Goldmann (2001), the notion of minority "may be defined on the basis of a variety of factors such as ethno-cultural characteristics (e.g. ethnic minorities), demographic characteristics (e.g. the elderly), (. . .)" (Goldmann, 2001, p. 206), and thus it can include a larger pool of long-established minority people. It should also be noted that the relative size of the foreign-born population may not reflect the actual number of foreigners because many of those born outside of the country in which they reside may be undocumented. Thus, they may be not included in the actual statistics on the number of foreigners.
7. In addition to racist and xenophobic crimes, some nations offer data on hate crimes that are motivated by anti-Semitism, sexual orientation, extremism, religious intolerance, Islamophobia, anti-Roma, disability, gender identity, and other/unspecified category (European Union Agency for Fundamental Rights [FRA], 2012b). Between the nations under investigation, only Sweden and Finland offer data on most of the hate crime categories outlined above (FRA, 2012b). Apart from these categories, there are no available data on group-specific hate crime directed toward other minorities (such as German minorities in Belgium or Finnish minorities in Sweden).

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Measuring the "Unmeasurable": Approaches to Assessing the Nature and Extent of Product Counterfeiting

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Abstract

Due to its considerable negative consequences, product counterfeiting is a global problem that is a growing concern for consumers, government entities, law enforcement, and businesses. Unfortunately, current assessments of the nature and extent of the problem are largely unreliable and based on methodologies with significant limitations. This article examines the current approaches to measuring product counterfeiting, complementing those with a review of methods used to examine other crimes. It concludes by discussing the applicability of both commonly used and novel research methodologies, as they might apply to the study of product counterfeiting.

Keywords

product counterfeiting, measurement, estimation, methodology, brand protection

Introduction

Product counterfeiting is a growing, global problem that is of great concern to consumers, government entities, law enforcement, and businesses. This crime involves a range of illicit activities relating to the infringement of intellectual-property rights linked to consumer goods (Organisation for Economic Cooperation and Development [OECD], 2008). A wide variety of products are targeted for counterfeiting, and research and practice indicate that all forms of products are at risk (Heinonen, Spink, & Wilson, 2014; Nasheri, 2005), including batteries, pharmaceuticals, food and beverages, medicine and medical devices, children's toys, electronics, weapons, tobacco, gas and chemicals (as well as their storage tanks), luxury goods, and even nuclear power plant components

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(see, e.g., Albanese, 2011; Fenoff & Wilson, 2011; Harris, Stevens, & Morris, 2009; Heinonen et al., 2014; Nasheri, 2005; OECD, 2008; Spink, 2012; Spink & Moyer, 2011; U.S. Consumer Product Safety Commission, 2007). Product counterfeiting can have devastating impacts on public health and safety, the economy, innovation, private sector stability, and national security. Businesses face both losses and threats to their reputation and innovation as a result of counterfeiting (Heinonen et al., 2014; Speier, Whipple, Closs, & Voss, 2011). Profits from counterfeit goods also fund a variety of criminal and terrorist activities (Albanese, 2011; Heinonen & Wilson, 2012; International Anti-Counterfeiting Coalition [IACC], 2005; Sullivan, Chermak, Wilson, & Freilich, 2014; U.S. Department of Justice, 2008). These ongoing concerns make the counterfeiting of consumer goods an important emerging research area.

In this article, we discuss how to better assess the nature and extent of product counterfeiting. Given there is no "best" way to measure product counterfeiting, we highlight a number of potential approaches and their strengths and limitations. This overview of the various levels of measurement, units of observation, and types of methodologies is meant to provide guidance for those conducting the measurement to choose an approach most appropriate to their specific goals, context, and circumstances. We begin by reviewing definitions and estimates of the problem. We then review methods that have been used to estimate the extent of the problem. We also review methods used to assess other difficult-to-measure crimes and how they might be applied to product counterfeiting. We conclude by drawing lessons from this review and identifying promising approaches to estimating the nature and extent of product counterfeiting.

Defining and Measuring Product Counterfeiting

Product counterfeiting has a variety of loosely related definitions. Cordell, Wongtada, and Kieshnick (1996, p. 41) define it as "any unauthorized manufacturing of goods whose special characteristics are protected as intellectual property rights (trademarks, patents, and copyrights)." This definition incorporates unauthorized manufacturing but does not include other counterfeiting activities, such as repackaging defective or excess materials, which should have been destroyed by the manufacturer but were instead sold outside legitimate supply chains. This definition also differs from legal definitions such as that of the Trademark Counterfeiting Act (TCA) of 1984, which defined counterfeiting only as a trademark infringement (with copyright, patent, and trade secret infringement reflecting other types of intellectual property violations). The World Trade Organization (2015, p. 1) states that product counterfeiting involves "unauthorized representation of a registered trademark carried on goods identical or similar to goods for which the trademark is registered, with a view to deceiving the purchaser into believing that he/she is buying the original goods." The U.S. Food and Drug Administration (2007) defines product counterfeiting to include parallel trade and product diversion (the sale of goods in markets unintended by the brand owner). In our discussions, we keep the TCA's definition, focusing on the improper use of a trademark, foremost in mind, but stress only that how one wishes to define counterfeiting will help determine the best method to measure it. Several other issues compound these definitional challenges. One is the interchangeable use of similar terms (e.g., piracy, fraud) with product counterfeiting. For the purposes of this article, we focus only on trademark counterfeiting and exclude other forms of intellectual property theft, such as piracy, copyrights, and trade secrets. Legal definitions may also vary by state, country, and other jurisdictions.

Academic discourse on the definition of product counterfeiting has been limited as has been quality research on measuring its extent. Most studies cite common sources or publications as a reference point. Table 1 presents some widely cited estimates and their sources. These vary greatly in what, exactly, they measure (e.g., global value of counterfeit products, lost tax revenues in a single jurisdiction).

Table 1. Commonly Cited Estimates of the Impact of Product Counterfeiting and Their Sources.

Estimate of Counterfeiting Impact	Source
US$200 billion to US$600 billion to U.S. businesses/in world trade annually	Chaudhry and Zimmerman (2009); IACC (2005); U.S. GAO (2010)
US$1 billion in annual tax revenue lost due to counterfeit products in New York City	Thompson (2004)
US$400 million in annual tax revenue lost due to counterfeit products in Los Angeles	Freeman, Sidhu, and Montoya (2007)
Average 13 months in investigation time for counterfeit incidents in Michigan	Heinonen and Wilson (2012)
US$39 billion in annual revenue for American prescription-drug companies	Bate (2008)
US$3 billion in annual revenue for U.S. automotive parts manufacturers	Motor and Equipment Manufacturers Association (2009)
US$60 billion in annual losses	U.S. International Trade Commission (1984, 1988)
5–7% of world trade	Counterfeiting Intelligence Bureau (1997)
US$5 billion to US$30 billion in annual losses	Abbott and Sporn (2002); Stern (1985)

Note. IACC = International Anti-Counterfeiting Coalition; GAO = Government Accountability Office.

Much of what is known about the effects of product counterfeiting is derived from anecdotal accounts, case studies with limited generalizability, and unreliable methodologies (National White Collar Crime Center, 2004; Piquero, 2005; U.S. Government Accountability Office [GAO], 2010). This presents concerns with the accuracy and quality of current estimates. Chaudhry and Zimmerman (2009) contend that while the first step in understanding the counterfeiting problem is to establish the size of the counterfeit market, there is no way to directly measure the trade in counterfeit goods due to the illegal nature of the activity. The U.S. Government Accountability Office (2010, pp. 16–17) summarized this challenge as follows:

> Quantifying the economic impact of counterfeit and pirated goods on the US economy is challenging primarily because of the lack of available data on the extent and value of counterfeit strategies ... Because of the lack of data on illicit trade, methods for calculating estimates of economic losses must involve certain assumptions, and the resulting economic losses must involve certain assumptions, and the resulting economic loss estimates are highly sensitive to the assumptions used.

Methodologies used in previous assessments, including those most frequently cited (Counterfeiting Intelligence Bureau, 1997; OECD, 2008; U.S. Federal Bureau of Investigation (FBI), 2005), are generally not provided or are unreliable or invalid. Even where methods are provided, other limitations prevent a comprehensive estimate. For instance, Freeman, Sidhu, and Montoya (2007) used enforcement seizure data to estimate the extent of counterfeiting, but, as Chaudhry and Zimmerman (2009, p. 7) caution, seizures likely reflect only a small proportion of counterfeit trade. While such an approach can be useful for providing a base level of counterfeiting (U.S. GAO, 2010), it does not approximate the true extent of the product counterfeiting problem. Additional methods have included surveys of supply and demand (e.g., Rob & Waldfogel, 2006), economic multipliers to estimate effects on the U.S. economy (e.g., Siwek, 2007), statistical modeling (e.g., Hui & Png, 2003; Oberholzer-Gee & Strumpf, 2007), and triangulation methods incorporating the extrapolation of seizure and international trade data as well as the merging of both types of data in econometric models (e.g., OECD, 2009).

A review of methods seeking to foster best practices in data collection regarding product counterfeiting in specific industries suggested that such measures focus on consumption, using volume in potential units of measurement and clarifying the geographic area of coverage for the estimation (Centre for Economics and Business Research, 2002). Those seeking to measure counterfeits should clarify their unit of analysis and measurement a priori. In other words, before estimating or measuring counterfeiting, researchers should consider two questions:

(1) What is the level of estimation?
(2) What is the unit of observation?

Answering these questions will point to specific methodologies and types of measurements for the aspect of product counterfeiting to be estimated. Researchers could examine product counterfeiting by time period, geographic location, industry, brand, or product. Potential units of observation include offenders; schemes; general consumers; and consumers as victims, brands, or products. We discuss these questions in more depth subsequently.

Levels of Estimation

Identifying the level of estimation is the general focus for determining what is to be estimated, why it is important to make the estimation, and how the estimation is established. While the unit of analysis is the main entity being analyzed, the level of estimation narrows the scope for which the main entity is examined. For example, if the unit of observation is the product being counterfeited, a researcher could examine the number and type of products by time period, geographic location, industry, brand, or product. Numerous approaches to each level of estimation are possible depending on the needs of those making the measurements. We review each of these characteristics below.

Time period. Researchers may first be interested in determining the prevalence of product counterfeiting across time. Longitudinal studies are important for estimating trends of product counterfeiting to determine how the problem is changing and evolving. These studies may also focus on identifying differences in the prevalence of product counterfeiting following major events or interventions. There are likely different trends across products, locations, brands, or industries. Numbers of victims or offenders are also likely to change over time.

Geographic location. In other cases, researchers may want to know about the prevalence of product counterfeiting by location, such as by local communities or cities, states, countries, or even globally. They may be interested in whether counterfeiting by industry, brand, or product is more prevalent in one location than another or whether the characteristics of victims or offenders vary by location or just in how prevalent counterfeiting is in a given location.

Industry. Industry estimates are common and may involve identifying the number of products, brands, offenders, or victims for an entire industry. Such estimates may also attempt to document whether some industries are more susceptible to counterfeiting than others.

Brand. A firm may try to determine the extent of counterfeiting of its brands to assess where its counterfeiting problem lies. For example, brand estimates could include losses of legitimate sales due to the purchase of counterfeits in the marketplace or brand damage (in terms of money or reputation). Researchers could focus on establishing the extent of counterfeiting of individual brands to assess brand susceptibility to counterfeiting. Estimates could also be made across brands from different companies.

Product. A final level of product counterfeiting estimation examined here is the product itself. This could include, for instance, the number or wholesale or retail value of products. One possible focus is the level of counterfeiting for a specific product type. Another focus is to compare across products so as to determine which products are more susceptible to counterfeiting. Estimations focusing on the product level can help researchers to identify the characteristics of products most likely to be counterfeited.

Units of Observation

Once the level of estimation has been established, the unit of observation must be determined. The unit of observation is what is being studied. It is the population being observed and the exact measurements taken to determine prevalence levels of product counterfeiting. The specific research questions will determine the various characteristics of the main unit of observation to document. Below we examine six potential units of observation for determining the prevalence of product counterfeiting: offenders, schemes, general consumers, consumers as victims, brands, and products.

Offenders. Crime occurs when individuals decide to engage in illegal behavior. Offenders in product counterfeiting include anyone involved in the production, trafficking, distribution, accounting, or any other role related to the counterfeiting of material goods. Whether this includes only those criminally charged or others known to be involved in counterfeiting operations depends on the specific operationalization measure. The value of choosing individuals as the unit of observation is that individuals, and their behaviors and characteristics, may be relatively easy to identify and measure. Using individuals as the unit of observation allows for an in-depth examination of those involved in product-counterfeiting schemes and can help determine the overall size of the problem. However, only focusing on individuals ignores the larger context in which offenders carry out their activities. Understanding the larger context is the advantage of the scheme as a unit of observation.

Schemes. The scheme expands beyond the individual offender to consider situational and organizational elements of crime. The scheme encompasses the same concept as the criminal event, where all the distinct elements of product counterfeiting operations are considered. The scheme is a holistic consideration of numerous aspects—including individual offenders, criminal activities, victims, and temporal and geographic variables—of product counterfeiting as a crime. A scheme represents a discrete product-counterfeiting operation, where every individual involved in the scheme is considered a member of the scheme. Schemes may involve multiple criminal offenses, geographic areas, and time periods due to the measurement of all the relevant activities necessary for executing it. By identifying the schemes within specific temporal and geographic limits, researchers can uncover the size of the overall product-counterfeiting problem. By collecting all available information on product-counterfeiting schemes and the actions taken against them, researchers can ask new and innovative questions about how interventions can be formulated and targeted.

General consumers. Estimates using consumers as the unit of observation are based on levels of consumption and the decision-making processes involved in purchasing counterfeit products. Such estimates would involve determining the number of consumers willfully purchasing counterfeits so as to determine the extent of the consumer market base. Such estimates could also involve determining the extent of counterfeit purchasing, both willful and unknowing, so as to assess the scope and scale of the sale and purchase of counterfeit goods. While many consumers knowingly purchase counterfeits, many others may not and instead can be counterfeit victims, representing another potential unit of observation.

Consumers as victims. Focusing on individual victims as the unit of observation focuses on the subset of consumers who have unwillingly purchased counterfeit goods and have been harmed by them in some way. The harm may simply be monetary loss due to obtaining useless counterfeits instead of the intended product but could also extend to physical injury or even death when the products do not perform as advertised or contain harmful or ineffective components (e.g., counterfeit pharmaceuticals). Because businesses, governments, and educational and other institutions also purchase goods, they, too, can become counterfeit victims. For example, a recent U.S. GAO (2012) report examined the dangers of potential counterfeits to the Department of Defense supply chain, missions, and weapon systems and ultimately on the lives of troops. We further review the strengths and weaknesses of victimization studies below.

Brands. Brands whose products are illegally copied and reproduced are another victim that can be observed to determine the prevalence of counterfeiting. Such observation could involve examining the number of brands that have been counterfeited or the frequency by which specific brands have been counterfeited through various methods. Specific means of observation can include official records, identifying and collecting counterfeits in various markets, or collecting data from firms. Similar methods can also be used to observe counterfeiting of individual products.

Products. A final unit of observation reviewed here is the product, which could also be conceived as another form of corporate victimization. Examining specific products identified as counterfeit can provide an estimation of the extent of counterfeiting not only for the products themselves but also for entire brands and even industries. As discussed above, some products may be more susceptible to counterfeiting than others. The extent of counterfeiting of specific products can be determined through counts of the products in industry or government data or by various other measurement approaches. We next turn to methods that may be applied to the above units of observations, including those that have been used to assess other difficult-to-measure crimes.

Measurement in Similar Research Areas

While researchers face unique challenges in estimating product counterfeiting due to the paucity of research in this area and the clandestine nature of the crime, other criminological and criminal justice research has faced similar difficulties and may offer applicable lessons. In fact, most crimes are difficult to measure accurately. Reviewing research on measuring other types of crime can help us better understand methods that may be applied to assessing product counterfeiting.

Commonly Used Research Methodologies

Among commonly used research methods to assess the extent of crime are (1) officially reported data and statistics, (2) victimization surveys, and (3) self-report surveys. While each of these approaches has benefits and shortcomings, they provide important perspectives on the prevalence of specific types of crime. We review the uses of each and how they might be used to measure product counterfeiting.

Officially reported data and statistics. One of the most common methods for measuring crime is the use of officially reported and recorded data and statistics. Such data are used to analyze many types of crime. Sources of official data on product counterfeiting may include state and federal crime reporting systems, seizure data compiled by customs and border patrol agencies, and other reporting mechanisms such as the Internet Crime Complaint Center, where consumers can report online victimization. Other potential data sources include those collected by various international agencies and organizations, such as INTERPOL, the IACC, and the National Intellectual Property Rights Coordination Center.

A drawback to official data is they likely represent only a small portion of the actual volume of crime. They reflect police activity and organizational/individual decision-making rather than actual rates of criminal activities in the society (Skogan, 1974). Such data have been criticized for being inaccurate or (in some cases) unusable (Kitsuse & Cicourel, 1963; Loftin & McDowall, 2010; Lynch & Jarvis, 2008; Seidman & Couzens, 1974).

Regarding the Uniform Crime Report statistics compiled by the U.S. FBI, for example, Seidman and Couzens (1974) found that police administrative procedures can greatly affect what is actually reported and that changes in administrative procedure can produce concerning variations across agencies and over time. MacDonald (2002) found that attempts to estimate the total cost of crime to society vary by the underlying assumptions used to develop the estimation equations and that even the highest estimates may be conservative. Such estimates may also be flawed by the number and categories of crimes that are included as well as the lack of common definitions and common understandings of crime across jurisdictions. Official data on product counterfeiting would have similar problems, as organizational methods and procedures greatly affect the development of estimations and measurements.

Official statistics do not include the "dark figure of crime" or crime victimization experiences not reported to the police and therefore not included in official counts. This problem may be even greater for product counterfeiting, given the limited focus on the problem by most law-enforcement agencies, as well as incomplete, inaccurate, or nonexistent records even when cases of counterfeiting are uncovered. Officially reported crime rates often vary widely from rates calculated from victimization surveys (MacDonald, 2002; Sims & Myhill, 2001). Many victims do not report their victimization because they do not know they have been victimized, they do not consider it a big enough issue to report, or they do not believe reporting the crime will do any good. Disparities between victimization and official statistics may be even greater for product counterfeiting, given the unique nature of the crime and the failure of victimization surveys to ask individuals about counterfeiting victimization or to ask firms about victimization. Many counterfeits are identified by firms or through seizures and do not reach the legitimate consumer market, meaning many identified cases of counterfeiting will not have associated consumer victims.

In addition to law-enforcement data, information is available through industry record keeping of products and brands subject to counterfeiting, including industry and trade associations and quality-assurance organizations (e.g., Underwriters Laboratories and the International Organization for Standardization). Industry records of investigations and information regarding potential counterfeit operations provide an alternative perspective from those publicly available or investigated by government officials. Yet much like official statistics from government sources, these data are highly unpredictable, as company brand protection, investigation, and record-keeping practices vary tremendously. Companies may also be reluctant to share the information for a variety of reasons, including protection of trade secrets, distrust of external researchers, and fear of the publication of the risk to specific products or brands or brand protection efforts.

Private data do have the advantage of not relying on governmental resources and of providing a different picture than publicly available information or intelligence data. While this information can be obtained through surveys (described further below), researchers may also seek to collect these data on a wide scale across companies and industries in order to supplement government statistics and create a more complete picture of the scope and scale of product counterfeiting.

Victimization surveys. Victimization surveys are another commonly used research method for estimating the extent of crime. Victimization surveys (theoretically) account for the dark figure of crime through interviews of those who have been victimized regardless of whether they have reported their victimization experiences to the police. Victimization surveys allow respondents to discuss what has happened to them, improving the quality of information. Victimization surveys allow for the estimation of victimization risks, responses, and consequences (Cantor & Lynch, 2000). They also allow researchers to examine the differences between victims who do and do not report their victimizations to the police.

Unfortunately, there are discrepancies between individual perceptions of victimization experiences and what the police might record as a victimization experience. Respondents' lack of knowledge regarding the laws governing product counterfeiting and their own victimization status hinder efforts to obtain accurate estimates of product counterfeiting (Heinonen, Holt, & Wilson, 2012). A lack of clarity on definitions of different crime categories can create confusion and ambiguity in response patterns (as caused, e.g., by individuals indicating that they were robbery victims when their house was burgled). The key difficulty in getting accurate information on areas such as human trafficking, terrorism, and product counterfeiting is that the activities are covert and the victims are difficult to find, so many survey samples may be unable to identify a sufficient number of victims for analysis.

Despite these potential limitations, some studies have begun to explore the prevalence of product counterfeiting through victimization surveys. Spink and Heinonen (2012), for example, surveyed a representative sample of nearly 1,000 Michigan residents about their experiences with counterfeit products. More than 1 in 10 respondents reported purchasing a product that they thought was authentic but was instead counterfeit. Bush, Bloch, and Dawson (1989) similarly surveyed a sample of manufacturers with a net worth greater than US$500,000 and with membership in the IACC. Of the 103 firms that responded to the survey, about half reported their product(s) had been counterfeited. Large firms were more likely to report such victimization than small ones: Only 26% of firms with annual sales less than US$10 million reported such victimization, compared to 71% of firms with annual sales exceeding US$50 million. Although the precise sampling method for this survey and hence its generalizability is not clear, it highlights how surveys may be used to measure product-counterfeit victimization and its variation. Numerous other approaches are possible, including surveys of consumers similar to surveys of the general population such as the National Crime Victimization Survey or the International Crime Victimization Survey.

Self-report surveys. Self-report surveys entail surveying or interviewing individuals on whether they have committed a certain type of crime. The value of self-report measures has long been recognized in criminology, with many important data collection efforts using this approach (Thornberry & Krohn, 2000). Offending surveys measure the frequency and the type of offending behaviors over a period of time with the goal of identifying the prevalence of offending. By gathering a representative sample of the population, such surveys can enable rough estimates of the prevalence of individual offending behavior. There are several disadvantages to self-report surveys, including the reliability of self-reporting and the cost of obtaining a sufficient sample to extrapolate to the larger population. Reliability can vary with recall error and either fabrication of offenses or reluctance to report offending.

Self-report surveys are valuable for obtaining offending estimates, especially in light of the level of consumer complicity in product counterfeiting. Indeed, consumer demand is a main driver of the counterfeit market (Wilson & Kinghorn, 2015), and, as reviewed by Staake, Thiesse, and Fleisch (2009), many studies have been conducted on demand-side investigations. Self-report surveys have been used to build an extensive literature assessing consumer attitudes toward product counterfeiting and factors influencing intentions to purchase counterfeits (e.g., see Albers-Miller, 1999; Bian & Moutinho, 2009; Bian & Veloutsou, 2007; Bloch, Bush, & Campbell, 1993; Business Action to Stop Counterfeiting and Piracy, 2009; Casola, Kemp, & Mackenzie, 2009; Chakraborty, Allred, & Bristol, 1996; Chaudhry & Stumpf, 2011; Chaudhry & Zimmerman, 2009; Cordell, Wongtada, &

Kieschnick, 1996; Furnham & Valgeirsson, 2007; Penz & Stöttinger, 2008; Phau & Teah, 2009; Swami, Chamorro-Premuzic, & Furnham, 2009; Teah, Phau, & Huang, 2015; Tom, Garibaldi, Zeng, & Pilcher, 1998; Veloutsou & Bain, 2008; Vida, 2007; Wee, Tan, & Cheok, 1995; Wilcox, Kim, & Sen, 2009; Yoo & Lee, 2009). Self-report surveys have also been used to assess managerial perspectives on counterfeiting problems and potential solutions (see Bush, Bloch, & Dawson, 1989; Chaudhry & Zimmerman, 2009; Chaudhry, Zimmerman, Peters, & Cordell, 2009; IP Crime Investigators College, 2015).

To assess counterfeit offending behavior, self-report surveys on product counterfeiting could ask consumers whether they have knowingly purchased a counterfeit product or have produced, distributed, sold, or otherwise been involved in a counterfeiting scheme. For example, James and Lemon (2013) surveyed a nationally representative sample (n = 1,073) of UK consumers about their purchasing behavior and perspectives, finding more than half reported purchasing some form of counterfeit product, with 18% reporting they had purchased counterfeit alcohol and 16% reporting they had purchased counterfeit pharmaceuticals. While such surveys do have limitations, as noted, they offer a unique way to assess this crime that may complement other approaches.

Novel and Innovative Research Methodologies

In addition to the commonly used methods outlined above, several other novel and innovative approaches may be useful for examining the nature and extent of product counterfeiting. These methods are growing in popularity and have great potential when applied to product-counterfeiting crimes. While not all directly measure prevalence, they can help advance understanding of product counterfeiting, thereby pointing to new directions for developing more complete and accurate measurements. These methods include use of (1) open-source data, (2) ethnographic and snowball sampling, (3) respondent-driven sampling (RDS) and related methods, (4) script and network analysis, and (5) simulation studies. We review each of these below.

Open-source data. An increasingly used method to examine the extent of difficult-to-measure crimes involves searches of open-source materials. These searches can include information from government databases, court records, law-enforcement reports, news articles, academic journals, private watch groups, and industry and professional associations. Triangulation of multiple data sources overcomes the limitations of single sources, reducing the chances of bias and increasing reliability and validity (Chermak, Freilich, Parkin, & Lynch, 2012). Overcoming the limitations of a single source is a very attractive feature of using multiple open sources, allowing for the collection of information on every available crime. Ideally, researchers would clearly identify the inclusion and exclusion criteria prior to the searches and then use trained searchers to find the relevant materials. Once materials are selected for inclusion, they are coded and entered into a database for analysis. This approach has been used to study human trafficking (Kutnick, Belser, & Danailova-Trainor, 2007; Wilson & Dalton, 2008), terrorism and extremism (Chermak et al., 2012; Freilich, Chermak, Belli, Gruenewald, & Parkin, 2014), and the intersection of product counterfeiting and terrorism (Sullivan et al., 2014).

One such effort at using this method to study product counterfeiting has been the Michigan State University Center for Anti-Counterfeiting and Product Protection (A-CAPP) Product Counterfeiting Database, which assembles information on crimes involving counterfeit products committed in the United States (Heinonen & Wilson, 2012; Sullivan et al., 2014; Wilson & Heinonen, 2010, 2011). In building the database, A-CAPP researchers reviewed more than 3,100 documents from industry, government, media, scholarly, and still other sources. This research identified more than 800 product counterfeiting schemes in the United States since 2000 involving a large number of different products.

While open sources can be useful for building information and data for measuring product counterfeiting, they do not address the dark figure of crime. Open-source searches are limited to incidents that have been identified in publicly available materials, subjecting them to publication and selection bias. To establish a manageable breadth of scope, open-source searches are typically limited to indicted crimes. As a result, an open-source search on product counterfeiting may not include those identified by the government or industry but who have not been made public. Despite these limitations, analysis of product-counterfeiting crimes through open-source databases can be a powerful way to make informative recommendations for policy and practice.

Ethnography and snowball sampling. Ethnography and snowball-sampling techniques have been used, where the populations of interest might otherwise be difficult to access (e.g., street criminals—Anderson, 1999; police officers—Manning, 1997, 2008; Moskos, 2008; narcotics markets—Goffman, 2014; Williams, 1989). Ethnographic work is based on methods frequently used in anthropology but has been applied across a variety of disciplines and subjects. In ethnographic research, the researcher takes on the role of a participant observer and becomes embedded in the specific group of interest. The initial stage involves obtaining access, which is often the most difficult to navigate. The researcher must find an individual affiliated with the group under study and gain his or her trust to a degree that a gatekeeper is willing to expose the researcher to his or her affiliates. This form of pseudo-snowball sampling continues until meeting additional gatekeepers who provide more access and exposure to others. Once trust is established, the researcher can record his or her experiences and interactions. This is particularly useful with difficult-to-reach populations as well as organizations not normally accessible to researchers. After prolonged exposure, observed behaviors and social interactions become more normal and representative of routine, everyday experiences.

Applying this technique to examine product counterfeiting would be challenging but highly beneficial. While identifying and accessing an initial gatekeeper would be most challenging, once access is established, the quality and richness of the resulting data can provide greater understanding of the intricacies of product-counterfeiting networks, production, and culture. The nonprobabilistic nature of snowball sampling, however, limits its ability to estimate the true prevalence of product-counterfeiting activity except in particularly defined circumstances. Supplementing this method with others can greatly enhance the ability of researchers to measure the nature and extent of product counterfeiting.

RDS and related methods. RDS is an intriguing research strategy that has been used to study human trafficking. RDS was developed by Heckathorn (1997) in an attempt to address limitations with snowball-sampling (and related) methodologies. RDS is similar to snowball sampling, informant sampling, and target sampling but applies a more rigorous method to allow extrapolation to the larger population or subpopulation being studied. RDS is also appropriate, where traditional snowball-sampling techniques are either not possible or successful. RDS relies on a structured referral process with a Markov property to achieve diversity and equilibrium (Zhang, 2012). This is accomplished through successive waves of participant recruitment and the use of incentives and a systematic recruitment process. Using these methods, the researcher is ultimately able to make inferences about the target population from the initial convenience sample (Zhang, 2012). The use of RDS allows researchers to use preexisting social networks to develop a sample of the subpopulation of interest. While it has been challenged as nonprobabilistic, as it is based on an initial convenience sample (Heckathorn, 2002), the method is believed to allow an unbiased estimation of the target population (Volz & Heckathorn, 2008).

A similar method was used by Maguire and colleagues to examine child sex trafficking in the Philippines (Maguire & Gantley, 2010; Maguire, Gantley, & Snipes, 2009; Maguire & Snipes, 2007). Their approach used 10 people (8 investigator/researchers, 1 data collection expert, and 1 security expert) to collect data. The investigators each spent seven to eight nights visiting bars, brothels, massage parlors, and other sex trade hubs over three waves gathering information by posing as "sex tourists" and seeking out minors who were either prostituted or commercially exploited. They would approach intermediaries such as taxi drivers and bellhops and request locations where they could find prostitutes. They then submitted data on each encounter to a central hub by voice or text message. Using this methodology, they observed 1,550 commercially exploited or prostituted young women and girls and confirmed that 103 of these were minors. Although it provided rich data, ethical and safety concerns have been raised regarding this particular research.

Similar strategies could be used with product counterfeiting by observing areas known as "hot spots" for counterfeit goods and systematically identifying and interviewing individuals linked to the buying and selling of counterfeits. The goal of such research would be to find others in the counterfeit market at different levels of the supply chain, branching from an initial starting point to create a more fully developed picture of different markets. These data collection techniques could also be used in conjunction with script and network analyses.

Script and network analysis. The "crime script" approach allows researchers to examine how a specific type or category of crime is committed in an effort to identify its key events and roles (Cornish, 1994). Different crime categories result in different crime scripts, and these scripts can be useful in identifying the routine activities involved in the commission of different types of crimes and in developing prevention and intervention approaches (Cornish & Clarke, 2002). Product counterfeiting occurs in a manner similar to drug crime and cybercrime in that it can include organized criminal activities and networks with organizational structures, numerous perpetrators, and multiple jurisdictions over extended periods of time, challenging the ability of researchers to study these criminal activities. Crime scripts can be used to further understand how product counterfeiting occurs and therefore guide researchers to specific areas to search and identify counterfeiting-related activities, thereby improving researchers' ability to estimate the true extent of the problem.

Script analysis can be used in conjunction with network analysis to examine the different roles that are essential to committing the various elements of product counterfeiting schemes and offenders carrying out those specific roles. Cornish and Clarke (2002) demonstrate that it is possible to examine the choices and actions that occur throughout the crime script, allowing researchers to better understand the roles that different individuals in the criminal network might take on. This typically involves a series of networks (both legitimate and illegitimate) that are interconnected and where individuals vary in their levels of criminal involvement. To use a network-based approach, researchers can identify a starting point and follow the network, as they would in a snowball or respondent-driven sample, to develop a complete network of all those linked to the original "seed" individuals. Alternatively, researchers may collect data on all those involved in product counterfeiting who meet a specific set of criteria (e.g., offenders involved in the counterfeiting of pharmaceuticals that passed through pharmacies in France from 2014 to 2015). Systematic documentation of the involvement of these networks can aid researchers and practitioners in developing a more complete understanding of network breadth and depth, thereby creating more accurate estimates of the prevalence of product counterfeiting.

Simulation studies. More recent criminological and criminal justice research has used simulation modeling approaches to study crime. These approaches apply simulation models commonly used in computer science (and video gaming), weather prediction, geography, and geology to the study of crimes such as street robbery (Groff, 2007a, 2007b) as well as police responses to crime (e.g., Groff & Birks, 2008). Simulation models combine known data with decision-making models to predict how patterns (in weather, geologic activity, migration, or human behavior) will emerge and evolve. Simulations can also be used to predict how individuals in product-counterfeiting networks interact and adapt over time, either when uninhibited or facing anti-counterfeiting measures.

Simulation models address concerns related to inadequate data, data quality, and appropriate available methods (Groff, 2007a). Often simulation models are used where researchers cannot easily manipulate conditions (e.g., physical environment or social interactions) without incurring prohibitive expenses or where manipulation might be unethical (e.g., random assignment to poverty, middle-class, and upper-class groupings). Instead, a series of variables are used to extrapolate what would likely occur in different circumstances.

Key challenges in simulation-modeling techniques relate to the availability of micro-level data on individual behavior as well as methods appropriate for capturing and modeling spatial and temporal dynamics on interactions among offenders, victims, and guardians (Groff, 2007a). Groff (2007a, 2007b) merged agent-based modeling techniques with geographic information systems to test routine activities theory as it applies to street robbery. This work, combined with that of Groff and Birks (2008) examining police-response tactics, demonstrates the potential efficacy for simulation modeling techniques, where access to data is limited or incomplete and modeling human interaction may be difficult.

Lessons Learned: New Directions in Product Counterfeiting Research

Existing estimates of product counterfeiting suffer various methodological shortcomings. Too often, insufficient information exists on how commonly cited estimates were developed and on how accurate or appropriate these estimates might be. Techniques such as analysis of official data, victimization surveys, and self-reports commonly used in other areas of criminology may help establish a low-end estimate of product counterfeiting but are likely to fall short of estimating its true extent. More novel techniques for estimating difficult-to-measure crime show promise for assessing product counterfeiting but also have limitations. Each of these techniques will offer valuable perspectives on the nature and extent of product counterfeiting due to their unique characteristics and approaches.

A number of key concerns and challenges still need to be addressed when attempting to assess the nature and extent of product counterfeiting. These concerns can impact measurement attempts in several ways. For example, there are difficulties in accessing useful information. Brand owners and law enforcement organizations typically do not publicize or share the level of data (if any) necessary for developing useful measures (or studying the nature of the crime and its harms and victims). Existing sources of information are limited at best. Many companies fail altogether to recognize their product counterfeiting risk (Wilson & Kinghorn, 2014), so they may not even gather useful data on the problem. Victims of product counterfeiting also might not know that they are victims, and if they do know, they might not care or be willing to share information.

Attempts to access information through law enforcement and government entities also present significant challenges. Product counterfeiting is often not a priority for law enforcement and prosecution agencies, which decreases the likelihood of successful detection and prosecution. While enhancing awareness through training and education on these issues could aid law enforcement in detecting incidents, concerns with the accuracy of record keeping and official reports on the criminal justice system may still limit the reliability of these data.

The final challenge that needs to be addressed involves access to those who engage in product counterfeiting. Some researchers attempt to examine crime problems through interviews with those who have been incarcerated for committing particular crime. Interviewing prisoners who have been convicted of product counterfeiting and related crimes could be useful, but there are several limitations of this approach. Prisoners would only represent the (likely small) portion of product counterfeiters who have been caught, charged, and convicted of the crime. At each stage, there is a funnel effect, where the remaining group is an increasingly smaller portion of the total population of product counterfeiters. Furthermore, these individuals may have lingering loyalties to the counterfeiting networks in which they are involved. Out of loyalty and interests in avoiding further harm to these networks or themselves, they may be unwilling to share information that could implicate others. This concern also relates to the difficulty in identifying and accessing gatekeepers who might be the most useful contacts for ethnographic analysis of product-counterfeiting networks and cultures. This raises the question, and need for research, on whether accessible individuals are part of mainstream society or are isolated in a manner similar to some terrorist cells in an effort to protect the larger network.

While the approaches we have suggested to estimate the nature and extent of product counterfeiting are far from perfect, they can enhance or supplement existing methods. They may be most fruitful when the level of estimation and unit of analysis are specifically articulated and consistent with the method. To help offset the shortcomings of specific methods, future attempts may seek to use multiple methods to assess the nature and extent of product counterfeiting. Doing so may provide a more complete picture of the overall product-counterfeiting problem.

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