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Gentrification, Neighborhood Change, and Crime Across Milwaukee

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GENTRIFICATION, NEIGHBORHOOD CHANGE, AND CRIME ACROSS MILWAUKEE

by

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ABSTRACT

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Data from 247 census tracts and 592 block groups in Milwaukee, Wisconsin were analyzed to determine the extent of gentrification across Milwaukee and the effects of neighborhood change on both property and violent crime rates. The data are from 2010 and 2018 and captures the city's transformation over the majority of the past decade. Using frequency analyses, OLS regression, spatial lag regression and spatial error regression models, the relationships between gentrification, neighborhood change and crime are assessed. Similar to other quantitative research findings, this paper found very little evidence of gentrification in Milwaukee from 2010 to 2018. Regarding the effect of neighborhood change on changes in crime, very few of the variables included in models were statistically significant. At the census-level, changes in population density, median assessed housing value, and percent of housing units that were vacant all had statistically or marginally significant effects on the changed rate of property crime. Changes in the percent of renter occupied units and the percent of the population made up by "elderly" individuals (those 60 years and older) both had statistically or marginally statistically significant effects on the changed rate of violent crime. At the block group-level, changes in median assessed housing value and the percent of the population with at least a Bachelor's degree both had statistically significant or marginally significant effects on the

change in property crime rates and changes in population density and renter populations both had statistically significant effects on the change in violent crime rate. Based on these findings, the effects of neighborhood change vary based on the type of crime and the unit of analysis at which the variables are measured. The implications of these differences are discussed at length and offer plentiful opportunities for future research.

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Gentrification, Neighborhood Change, and Crime Across Milwaukee

Much of the past research on gentrification, neighborhood change, and crime has been conducted using data from large and high profile U.S. cities such as Chicago (Morenoff & Sampson, 1997; Morenoff, Sampson & Raudenbush, 2001; Sampson & Raudenbush, 2004; Immergluck & Smith, 2006; Chavez & Griffiths, 2009; Papachristos, Smith, Scherer & Fugiero, 2011; Smith, 2014), Los Angeles (Griffiths & Tita, 2009; Lee, 2010; MacDonald, Hipp & Gill, 2012), and New York City (McDonald, 1986; Barton, 2016). Consequently, the findings from this collection of research are most valid when referencing a city of this stature. Rather than use data from one of the aforementioned cities, the current study uses data from a mid-size and lesser-known U.S. city: Milwaukee, Wisconsin. With a population averaging just under 600,000 people over the past decade (U.S. Census Bureau), Milwaukee is comparably quite a bit smaller than cities dominating past gentrification and neighborhood change research. Generally speaking, mid-size cities undergo less intense, widespread gentrification and neighborhood change than larger cities (Landis, 2015; Maciag, 2015). Studying the effects of gentrification and neighborhood change on crime outcomes, in a less populous urban area, in which gentrification and neighborhood change are not abundant, may provide additional evidence regarding the relationships between gentrification, neighborhood change, and crime.

The research documented in this thesis explores this relationship using a two-step analysis. The first step to be undertaken for this project is to determine the extent to which gentrification occurs across Milwaukee census tracts[1] and block groups[2]. This will be investigated using an operational definition of gentrification based on past research (Maciag 2015); I will use a composite measure of median income and median housing value to identify gentrifiable neighborhoods in 2010, and a composite measure of the increase in educational attainment and median housing value to identify gentrified neighborhoods in 2018. Bostic and Martin (2003), Freeman (2005), and Barton (2016) have also used similar operational definitions. If there is sufficient gentrification across Milwaukee neighborhoods to reliably estimate its effects, the second step will be to perform multivariate regression analyses on the effects of gentrification and various neighborhood change measures on property crime rates and violent crime rates across Milwaukee neighborhoods.

The research questions will be answered using data from three sources. The data for the dependent variables (i.e. property crime rate and violent crime rate), was gathered from the Wisconsin Incident-Based Reporting System (WIBRS). Data for property crime rate and violent crime rate were separated into two dependent variables, as there is evidence that varying mechanisms affect different types of crime (Roncek, Bell & Francik, 1981; McDonald, 1986; Krivo & Peterson, 1996; Butcher & Piehl, 1998; McNulty & Holloway, 2000; Santiago, Galster & Pettit, 2003; Immergluck & Smith, 2006; Van Wilsem, Wittebrood & De Graaf, 2006; Lee, 2010; Kreager, Lyons & Hays, 2011; Papachristos et al., 2011). The data for the independent variables were collected from IPUMS and the U.S. Census Bureau American Community

[1] "Census tracts are small, relatively permanent statistical subdivisions of a county or equivalent entity that are updated by local participants prior to each decennial census…census tracts generally have a population size between 1,200 and 8,000 people, with an optimum size of 4,000 people. A census tract usually covers a contiguous area; however, the spatial size of census tracts varies widely depending on the density of the settlement." (U.S. Census Bureau Glossary)
[2] "Block groups (BGs) are statistical subdivisions of census tracts, are generally defined to contain between 600 and 3,000 people… a block group consists of clusters of blocks within the same census tract that have the same first digit of their four-digit census block number… a BG usually covers a contiguous area." (U.S. Census Bureau Glossary)

Survey. The data was reported at or transformed[3] to represent the 254 census tracts and 661 census block groups in the City of Milwaukee.

This research contributes to previous findings in three key ways. As previously stated, Milwaukee provides a unique setting to study gentrification, neighborhood change, and crime. As a mid-size city, it is an anomaly among the cities previously used to study these relationships. Another contribution of this research is that there is a systematic assessment of the presence or absence of gentrification in Milwaukee from 2010 to 2018. Brown-Saracino (2017) explains that quantitative and qualitative researchers disagree about the extent and effects of gentrification; this remains a highly debated point of contention. The systematic assessment of gentrification in Milwaukee provides further understanding of the presence or absence of gentrification in an understudied city. This research will also provide further insight into how gentrification or neighborhood change may influence different types of crime rates by using two dependent variables: property crime rate and violent crime rates.

LITERATURE REVIEW

Definition of Gentrification

Gentrification is a multi-faceted phenomena but is broadly defined as the "reversals in the concentration of urban poverty and structural decay… applies only to urban neighborhoods that underwent a period of substantial economic decline… increased middle- and upper-class residents accompany visible improvements to an area's real estate and local infrastructure" (Kreager, Lyons & Hays, 2011). This definition includes three key elements of gentrification. The first is that a neighborhood that can be gentrified must be characterized by disadvantage

[3] The crime data were reported using addresses. In order to have the data represent census tracts and block groups, the addresses were geocoded in ArcMap and property crime and violent crime rates were calculated based on the sum of geocoded crimes in each tract or block group.

("substantial economic decline"). The second is that the neighborhood that is gentrified experiences a rise in wealthier residents (the "gentry"). Finally, this influx of wealthy residents creates structural change of the neighborhood itself; this occurs for varying reasons, such as a higher degree of political clout from affluent residents and new businesses that cater to the wealthier population.

Theorists have debated about *why* gentrification occurs (Slater, 2011). Most scholars emphasize that gentrification embodies "class inequalities and injustices created by capitalist urban land markets and policies" (Slater, 2011, p. 571). Scholars date the phenomenon to the mid-twentieth century. In his book, *The Origins of the Dual City: Housing, Race, and Redevelopment in Twentieth-Century Chicago*, Joel Rast (2019) explains that gentrification began because unable to eradicate urban poverty, policymakers encouraged downtown and low-income "slums" to become "buffered" by neighborhoods occupied by the middle and upper-middle classes. This explains why gentrified neighborhoods are located between downtown and low-income neighborhoods, along with the time period in which cities across the country gentrified.

Debate on the Presence and Extent of Gentrification

Researchers have dedicated studies to determining the extent of gentrification across American cities. Brown-Saracino (2017) performed a literature review regarding the extent and effects of gentrification found by past scholars; there are two major competing viewpoints on gentrification as explained by Brown-Saracino (2017). Qualitative researchers and the media view gentrification as widespread and of great consequence (Brown-Saracino, 2017, pp. 517-519). Quantitative scholars, on the other hand, think of gentrification as sparse and of limited consequence (Brown-Saracino, 2017, pp. 519-525). She discovered that the majority of findings from quantitative research (such as those done by Hwang & Sampson, 2014; Hwang, 2015; Timberlake & Johns-Wolfe, 2017; Zuk, Bierbaum, Chapple, Gorska, & Loukaitou-Sideris, 2015) suggest that gentrification is scarce (Brown-Saracino, 2017, p. 522). Landis (2015, p. 3) also found that "[his analysis of] the 70 largest U.S. metro areas reveals that decline not upgrading was the dominant form of neighborhood socio-economic change between 1990 and 2010 [and] only 3% lived in pregentrifying neighborhoods." Maciag (2015b) observed that gentrification occurred in only 8% of census tracts across American cities and that the majority of these tracts were located in larger cities such as New York City and Philadelphia.

Gentrification in Research

Due to gentrification being such a multi-faceted phenomenon, operational definitions for quantitative research are varied. Researchers have measured neighborhood gentrification using the number of coffee shops (Papachristos et al., 2011; Smith, 2014), others have coded images of block faces from Google Street View to assess the extent of neighborhood change (Hwang & Sampson, 2014), some have relied upon census measures (Taylor & Covington, 1988; Covington & Taylor, 1989; Bostic & Martin, 2003; Freeman, 2005; Van Wilsem et al., 2006; Smith, 2014; Maciag, 2015; Barton, 2016), some have used survey data in which residents were asked about their perceptions of gentrification in their cities, (Wyly & Hammel, 1998; Kreager et al., 2011), and others have utilized other measures such as mortgage lending data (Lee, 2010). The operational definition used in this study mirrors that of some of the past research and will be examined in-depth in the subsequent sections of the paper.

Gentrification and Crime: Theoretical Mechanisms and Empirical Findings

Gentrification has been used as an explanatory factor in research in criminology based on its theoretical relevance. Social disorganization theory posits that gentrification will lead to an immediate increase in crime due to the disruption in collective efficacy caused by residential turnover (Kreager et al., 2011). However, through the development of new social ties, collective efficacy increases across time, crime will then decrease. Conversely, routine activities theory proposes that gentrification will lead to an increase in crime due to the conflict between the pre-existing less affluent residents and new more affluent residents (Taylor & Covington, 1988; Lee, 2010; Barton, 2016). The two theories mentioned above will be more thoroughly discussed below.

Social disorganization theory proposes a curvilinear relationship between gentrification and crime as time passes. Theoretically, crime should immediately increase as gentrification begins because of a lack of informal social control and collective efficacy as the population changes, but crime should then decrease as the population and informal social control and collective efficacy stabilize. Two key concepts relating to the effect of gentrification and crime are identified in this theory: collective efficacy and social control. Collective efficacy is "defined as the linkage of cohesion and mutual trust among residents with shared expectations for intervening in support of neighborhood social control" (Sampson, 2012, p. 127). To simplify Sampson's (2012) definition, collective efficacy is the ability to and assurance that community members will similarly identify and address deviance. Wikström and Sampson (2006) examine *how* collective efficacy is constructed and strengthened. They explain that "[collective efficacy is] fundamentally about *repeated* interactions and thereby expectations about the future… the key theoretical point is that networks have to be activated in order to be ultimately meaningful" (Wikström & Sampson, 2006, p. 39). In sum, collective efficacy is built and maintained through community engagement and the confidence and *expectation* that community members will act.

Social control is the realization of this expectation. As Sampson, Raudenbush, and Earls (1997) explain,

> Although social control is often a response to deviant behavior, it should not be equated with formal regulation for forced conformity by institutions such as the police and courts. Rather, social control refers generally to the capacity of a group to regulate its members according to desired principles- to realize collective, as opposed to forced, goals (p. 918).

There are two key elements of this definition: 1) social control is not necessarily formal; and 2) social control is predicated upon shared ideals among members of the same community (e.g. a desire for clean sidewalks, little to no crime, a quiet neighborhood, etc.). Social control can be realized in a variety of different ways including 911 calls, citizen complaints, physical interventions, and memberships in neighborhood watch groups. The specific influences that break down informal collective efficacy and social control are hypothesized to be racial heterogeneity, residential mobility, and concentrated disadvantage (Barton, 2016, p. 1184). These effects influence the ability to organize, to create a sense of community, and to promote neighborhood control. However, to reiterate, these destabilizing effects of neighborhood change and gentrification are expected to level out as time passes which will lead to an overall increase in social control and collective efficacy and an overall decrease in neighborhood crime.

Routine activities theory is also well-known in the literature on the relationship between gentrification and crime. Originating from Cohen and Felson's (1979) seminal article, routine activities theory surmounts that when (1) a suitable target, (2) a likely offender, and (3) a lack of capable guardianship converge in space and time, a crime is likely to ensue. Routine activities theory would suggest that as neighborhoods change (particularly during gentrification), there will be a breakdown of "guardianship as new residents are less familiar with the neighborhood and incumbent residents [may be] unwilling to act as capable guardians due to resentment" (Barton, 2016, p. 1184). This unwillingness and lack of capable guardianship are both indicative of weaker neighborhood social control and collective efficacy.

Past research shows contradictory findings regarding the effect of gentrification on crime. Some scholars have found a positive relationship between gentrification and crime (Taylor & Covington, 1988; Covington & Taylor, 1989; Atkinson, 2000; Van Wilsem et al., 2006; Lee, 2010). Specifically, Taylor and Covington (1988) found that when the gentrification process occurred faster, there was a larger increase in crime across those Baltimore neighborhoods than neighborhoods that did not gentrify and neighborhoods that gentrified slowly. Covington and Taylor (1989), using the same set of neighborhoods, elaborated on this by observing that the more drastic the neighborhood change caused by gentrification, the larger the increase in crime. Both Atkinson (2000) and Van Wilsem et al. (2006) identified that the mechanism driving increased crime was gentrification-induced displacement resulting in a lack of informal social control and low collective efficacy. Finally, Lee (2010) found support for routine activities theory in his observation of increased crime post-gentrification across Los Angeles neighborhoods. Overall, these researchers, besides differences in emphasis on particular theories (e.g. routine activities theory) or consequences (e.g. displacement), observed increased crime after gentrification.

Opposing these findings, other researchers have observed a negative relationship between gentrification and crime (McDonald, 1986; Sanchez, 2001; Lawrence, 2013; Barton, 2016). Based on a descriptive statistical analysis, McDonald (1986) found that neighborhoods in Seattle, Boston, San Francisco, New York City, and Washington D.C. experienced a decrease in "personal crime"[4] after the neighborhood was gentrified. Sanchez (2001) performed an ethnography in Portland about a neighborhood with high levels of prostitution that was gentrified. She explains that the new, more affluent, and politically powerful residents successfully advocated for a decrease in neighborhood sex work. Lawrence (2013) and Barton (2016) used regression to analyze the effect of gentrification on crime, both of whom found a negative relationship between the variables in Washington D.C. and New York City.

Other researchers have found that the effects of gentrification on crime may be moderated by other variables (Kreager et al., 2011; Papachristos et al., 2011; Smith, 2014). Kreager et al. (2011) focused on the interaction between time and gentrification relating to its effect on crime using social disorganization theory. They found support for the theory in Seattle neighborhoods, observing an initial increase followed by a decrease in crime throughout the gentrification process. Others have found that the effect of gentrification on crime varies across neighborhoods. For example, Papachristos et al. (2011) found that gentrification impacted crime differently based on the racial distribution of the Chicago neighborhoods they analyzed. They noted that, although gentrification reduced homicide across all neighborhoods regardless of racial composition, gentrification resulted in an increase in robberies in primarily Black neighborhoods, whereas robberies decreased in primarily White and Hispanic neighborhoods (Papachristos et al., 2011; p. 233). Lastly, research performed by Smith (2014) indicated that the type of gentrification influences whether gentrification results in an increase or a decrease in crime across Chicago neighborhoods. He looked at "three forms of gentrification- demographic shifts, private investment and state intervention" (Smith, 2014, p. 569)[5] and their effect on gang

[4] "These include the 'personal crimes' of homicide, rape, robbery and assault" (McDonald, 1986, p. 170).
[5] Demographic-based gentrification is measured as the changes in racial composition, educational attainment, socioeconomic status, etc. of the population. State-based gentrification is measured as the demolition of public

homicides. Based on his analysis, Smith (2014, p. 586) found that demographic-based and private-investment-based gentrification decreased gang homicides, but state-based gentrification increased gang homicides.

Neighborhood Change and Crime: Theoretical Mechanisms and Empirical Findings

Besides gentrification, neighborhood change overall has been thought to impact levels of crime. Neighborhood change is an imprecise and sweeping concept that captures processes of shifting neighborhood demographics, physical conditions, commercial entities, cultural identities, and other environmental or contextual variables. Temkin and Rohe (1996) lay out three models of neighborhood change: (1) ecological, (2) subcultural, and (3) political economy. They suggest a fourth synthetic model that combines the three aforementioned models. The ecological model generally assumes that the future of a neighborhood is dependent on that neighborhood's social status and spatial position, where more affluent neighborhoods that are close to amenities will be more stable and well-off (Temkin & Rohe, 1996, p. 160). On the other hand, the subculturalist model emphasizes that the strength of kinship networks and the residents' sense of community affect neighborhood well-being (Temkin & Rohe, 1996, p. 162). Lastly, the political economy model argues that neighborhood welfare is primarily influenced by outside actors which include, among others, "real estate and insurance agents, bankers, and public officials" (Temkin & Rohe, 1996, p. 163). Temkin and Rohe (1996) argue that these three models should be combined into a singular model that emphasizes that while the urban hierarchy is important for a neighborhood's fate, neighborhood stability is possible regardless of its social status and spatial position when that neighborhood has a strong cultural identity and political clout (Temkin & Rohe, 1996, p.

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housing. Lastly, private investment-based gentrification is measured using the number of neighborhood coffee shops (Smith, 2014, pp. 576-578).

166). Overall, neighborhood change is complex and can be viewed through a variety of differing frameworks.

Both Kirk and Laub (2010, pp. 442-443) and Fagan (2008, p. 84) point to the beginning of the study of neighborhood change and its impacts (e.g. on crime) to the Chicago School in the mid-20th century. In their review of the link between neighborhood change and crime, Kirk and Laub (2010) recount four broad types of neighborhood change besides gentrification laid out by Shaw and McKay (1942): (1) central city population loss and middle-class flight; (2) public housing; (3) home ownership and home foreclosure; and (4) immigration. Although these broad types of neighborhood change differ in their modes of impact, they all have a similar consequence: the disruption of stability within a neighborhood. Kirk and Laub (2010, pp. 456-459) explain that central city population loss and middle-class flight is primarily due to the migration from urban to suburban areas. They explain that “it is still true today that city-to-suburban moves are most common” (2010, p. 456) and this influences neighborhood social order. Public housing can also have destabilizing effects whether it is the siting of new public housing or the demolition of old public housing (Kirk & Laub, 2010, pp. 467-475). These events also create population turnover, therefore leading to residential instability. In the same vein, Kirk and Laub (2010, pp. 475-479) explain that home ownership and home foreclosure also lead to population turnover and instability. Additionally, “foreclosures may increase the supply of available targets for a property crime and available locations for prostitutes and drug users to congregate,” which may lead to an overall increase in neighborhood crime (Kirk & Laub, 2010, p. 478). Lastly, immigration also creates population turnover (Kirk & Laub, 2010, p. 479). Interestingly, however, scholars have found that increased immigration creates tight-knit residential enclaves with strong informal social control and collective efficacy due to cultural similarities and comfort (Kirk & Laub, 2010, p. 481). So, unlike the three preceding types of neighborhood change, immigration may actually foster increased neighborhood stability and a decrease in crime despite population shifts.

Fagan (2008, p. 101) lays out three major influences of neighborhood change on crime: 1) social interactions and social organization; 2) political economy; and 3) legal interventions. Social interactions and social organization are broadly understood by Fagan to be influenced by the willingness and capacity to build collective efficacy (2008, pp. 101-102). This is impacted by variables such as changes in the percentage of foreign-born residents, the percentage of renters and homeowners, and variables that measure affluence (poverty rate, unemployment rate, median income, etc.). Political economy, on the other hand, "includes both institutional forces and the effects of physical structures in the neighborhood" (2008, p. 102). Fagan notes that the political economy can be measured using a wide range of varying phenomena including changes in public housing and observational data on signs of physical disorder. (2008, pp. 102-106). Finally, Fagan (2008) explains that neighborhood-level legal interventions may also influence rates of crime. He says that legal interventions can be measured in a variety of ways including arrest rates and incarceration rates (2008, p. 107).

In their analysis of neighborhood change and crime, Butcher and Piehl (1998) authored one of three studies found in my review that assessed how *changes* in independent and control variables affected *changes* in dependent variables. They found that changes in neighborhood immigrant populations, racial and gender composition, unemployment, educational attainment, and income did not affect crime, but increases in total neighborhood population were related to decreases in crime (Butcher & Piehl, 1998). Like Butcher and Piehl (1998), Chavez and Griffiths (2009) did not find a relationship between changes in neighborhood foreign-born populations and changes in crime. However, they did distinguish between the foreign-born population and new migrants (regardless of their nativity) and found that "growth in recent arrivals occurs almost exclusively within the safest neighborhoods of the city" (Chavez & Griffiths, 2009, para. 1). Lastly, Santiago et al. (2003) observed that new development of public housing was not related to changes in crime.

Other researchers have evaluated how levels of independent and control variables at *one time* point affect changes in dependent variables in their analyses of neighborhood change and crime. Contrary to Butcher and Piehl (1998) and Chavez and Griffiths (2009), MacDonald et al. (2007) found a significant and negative relationship between large immigrant populations and changes in crime. They also found that a higher population density, larger Black population, higher residential mobility, fewer young males, and lower rates of poverty led to more significant decreases in neighborhood crime (MacDonald et al., 2007).

Some researchers have tested the effects of various neighborhood characteristics on crime at singular time points. Researchers have found mixed and, at times, contradictory results regarding the effects of various measures of neighborhood characteristics on crime. Studies have shown that higher population density is associated with lower crime (Roncek et al., 1981), higher population density is associated with higher crime (Immergluck & Smith, 2006), higher rates of unemployment and public assistance are related to higher rates of crime (Immergluck & Smith, 2006), higher neighborhood income is related to lower rates of crime (Immergluck & Smith, 2006), and more public housing is associated with higher crime (Roncek et al., 1981; McNulty & Holloway, 2000; Griffiths & Tita, 2009). Researchers have also noted that home foreclosures, the percentage of young males, poverty, number of businesses, divorce rate, and crime are positively related (Immergluck & Smith, 2006), that the percentage of female-headed households is associated with higher crime (Roncek et al., 1981; Immergluck & Smith, 2006), and concentrated disadvantage is related to higher crime (Roncek et al., 1981; McNulty & Holloway, 2000). In addition, Roncek et al. (1981) observed that a smaller elderly population, more high density housing buildings (defined by the researchers as having 10 or more units), increased household density, and an increased vacancy rate are all related to higher rates of crime.

Scholars have also found that certain neighborhood characteristics are *not* significantly related to crime. Studies have demonstrated a lack of a relationship between crime and the neighborhood gender composition (Roncek et al., 1981), the percentage of Spanish-speaking residents (Roncek et al., 1981), the number of neighborhood organizations/associations (Morenoff et al., 2001), social ties (Morenoff et al., 2001), and the ratio between adults and minors (Morenoff et al., 2001). Researchers have also tested the relationships between racial composition and crime, and residential mobility and crime. It has been observed that residential mobility affects certain types of crime (Immergluck & Smith, 2006), but that this relationship is mediated by factors such as concentrated disadvantage (McNulty & Holloway, 2000). Although some researchers have found that the percentage of Black residents and crime are positively related (Roncek et al., 1981; Immergluck & Smith, 2006), it has also been detected that the effect of racial composition on crime is mediated by concentrated disadvantage and the prevalence of public housing (McNulty & Holloway, 2000). This means that residential mobility and racial composition may be artifacts of poverty and disadvantage, which in turn has the ability to lead to these areas experiencing lower levels of informal social control. Overall, a wide variety of neighborhood change characteristics have been found to influence crime.

CURRENT STUDY

There will be two analyses addressed in this thesis: Analysis 1) Is there evidence of gentrification across Milwaukee census tracts and block groups from 2010 to 2018? And Analysis 2) What are the effects of gentrification (if adequately present in Milwaukee) and changes in various neighborhood characteristics on changes in property crime rate and violent crime rate across Milwaukee census tracts and block groups from 2010 to 2018?

To address analysis 1, I will use an operational definition of gentrification similar to those of past researchers (Bostic & Martin, 2003; Freeman, 2005; Maciag, 2015; Barton, 2016), in which the researchers first identify "gentrifiable" neighborhoods, then determine which of these gentrifiable neighborhoods were indeed gentrified. Similar to Barton's (2016) method, this measurement will be further validated using a simple content analysis. Lastly, a frequency analysis will be performed to understand the extent of gentrification across Milwaukee neighborhoods. As for analysis 2, four linear multiple regression models will be produced to ascertain the effects of gentrification (if adequately present in Milwaukee) and neighborhood change on changes in property crime rate and violent crime rate.

The present research proposes to advance past scholarly findings. First, this research project will identify gentrifiable neighborhoods in an effort to not artificially categorize already affluent neighborhoods as having gentrified. By defining neighborhoods as "gentrifiable," the accidental categorization of already affluent neighborhoods as having gentrified is avoided; this avoidance will make for a robust measure of gentrification. Second, to further ensure validity, a simple content analysis will be utilized to reference the neighborhoods in which gentrification has been said to occur based on the operational definition. The simple content analysis mentioned above, which will be based off of news pieces and scholarly sources, will hopefully provide support for the quantitative measure of gentrification used for this paper. Analysis 1 will also provide further insight into the academic debate on the extent of gentrification as outlined by Brown-Saracino (2017). This research also contributes to past findings, as the separate models for the different crime types will demonstrate whether gentrification (if present) and neighborhood change affect property crime rates differently than violent crime rates. Finally, the choice of Milwaukee neighborhoods as the unit of analysis is a contribution in of itself. Milwaukee's gentrification is unique when compared to other cities of focus in past research; whereas gentrification was profuse across cities like San Francisco and New York City, Milwaukee's gentrification has occurred in concentrated areas sporadically across the past couple of decades. This will provide an opportunity to understand changes in crime in neighborhoods that do not belong to cities having undergone swift and major transformation. Overall, this research will hopefully extend scholarly knowledge about gentrification, neighborhood change and its influence on crime.

DATA AND METHODS

Units of Analysis and Sample

The units of analysis for this study are census tracts and block groups. Although clustering tracts and block groups to form neighborhoods would be a theoretically stronger unit of analysis, many Milwaukee tracts and block groups are located across more than one neighborhood.[6] Clustering these tracts and block groups together may present issues as the neighborhoods may be further disjointed. In addition to testing the relationship between gentrification, neighborhood change, and crime, the present research will also perform a sensitivity analysis regarding the difference in the use of census tracts and block groups as neighborhood proxies. The "correct" or "most appropriate" proxy for neighborhoods is highly debated amongst quantitative researchers;

[6] Based on the Milwaukee Neighborhoods Identification Project.

various units of aggregation have been used across studies. Some social scientists have used census tracts (Bellair, 2000; Santiago et al., 2003; Immergluck & Smith, 2006; Chavez & Griffiths, 2009; Griffiths & Tita, 2009; Lee, 2010; Kreager et al., 2011; MacDonald et al., 2012), block groups (McNulty & Holloway, 2000; Sampson & Raudenbush, 2004), city blocks (Roncek et al., 1981), or other administrative boundaries (Taylor & Covington, 1988; Covington & Taylor, 1989; Butcher & Piehl, 1998; Morenoff et al., 2001; Van Wilsem et al., 2006; Papachristos et al., 2011; Smith, 2014; Barton, 2016). Hipp (2007) examined this debate by evaluating neighborhood effects on crime at the block and census tract levels. He concluded "that there is no single 'appropriate' level of aggregation. Rather, it appears that the effects of these structural measures can work at different geographic levels. Additionally, some constructs work at different geographic levels depending on the outcome being studied" (Hipp, 2007, p. 674). Census tracts and block groups were chosen for the units of analyses, not only due to the variation in proxies across past research, but also because both units of aggregation are theoretically relevant to the predictor and outcome variables. Characteristics of gentrification, neighborhood change, and changes in crime are significant at and may be visible at both the census tract and block group levels. The sensitivity analysis will examine differences in the coefficients at the census tract and block group units of analyses to test these neighborhood proxies.

There are 254 tracts and 661 block groups within Milwaukee city limits, but there were only 246 census tracts and 617 block groups included in analysis 1 due to missing data for 8 of the tracts (2.8% of the tracts) and 44 of the block groups (6.7% of the block groups). There only 246 tracts and 592 block groups included in the analysis 2 due to missing data for 8 of the tracts

(2.8% of the tracts) and 69 of the block groups (10.4% of the block groups).[7] Listwise deletion was chosen as the method for handling missing data as some of the data are spatially autocorrelated. Boehmke, Schilling & Hays (2015) explain that,

> With spatially correlated data we do not have separate observations since the realization of the dependent variable for one observation depends on the realization of the dependent variable in other observations. Thus, we can no longer assume that observations are independent and identically distributed. Ignoring this violation and applying multiple imputation as if observations are independent can, according to our simulation, lead to even more biased estimates than listwise deletion. (p. 2)

To summarize, the spatial autocorrelation in the data makes listwise deletion the least biased, feasible way to handle the missing data.[8] To ensure that the observations with missing values were missing at random, I measured the racial composition of each incomplete tract and block group (see Tables 1 and 2). There is a larger proportion of incomplete block groups that are majority-Black (41 of 69 block groups or 59.4% of the incomplete block groups). Overall though, based on the number of incomplete cases across racial distributions, the incomplete cases appear to be missing at random, which suggests that the estimates will not be biased further due to the nature of the missingness.

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[7] All 8 excluded observations at the tract unit of analysis were due to missing data on median assessed housing value. 43 block groups were missing data on median assessed housing value, 30 block groups were missing data on median household income, 1 block group was missing data on the percentage of renters, 1 block group was missing data on the percentage of vacant housing units, and 1 block group was missing data on the percentage of female-headed households.

[8] There is current work that suggests that kriging may be an appropriate alternative to multiple imputation for spatially autocorrelated data (Bleninger, 2017). Kriging is defined as "optimal prediction using spatial correlations. Information of neighbors is considered in the estimation by a spatial correlation function generating an interpolation over a spatial random process… the aim of kriging is not the estimation, but rather the prediction of values of unobserved regions" (Bleninger, 2017, p. 42). However kriging is not feasible for the timeframe of this thesis. It would be constructive to use kriging in the future and to compare the results to the estimates obtained using listwise deletion.

Table 1. Racial composition of incomplete census tracts

	Frequency
Majority-White	3
Majority-Black	3
Majority-Hispanic	1
Majority-Asian	0
Majority-Other	0
Integrated*	0

**Note: Integrated census tracts are census tracts where no racial group comprises more than 49.9% of the total population.*

Table 2. Racial composition of incomplete block groups

	Frequency
Majority-White	15
Majority-Black	41
Majority-Asian	3
Majority-Other	2
Integrated*	8

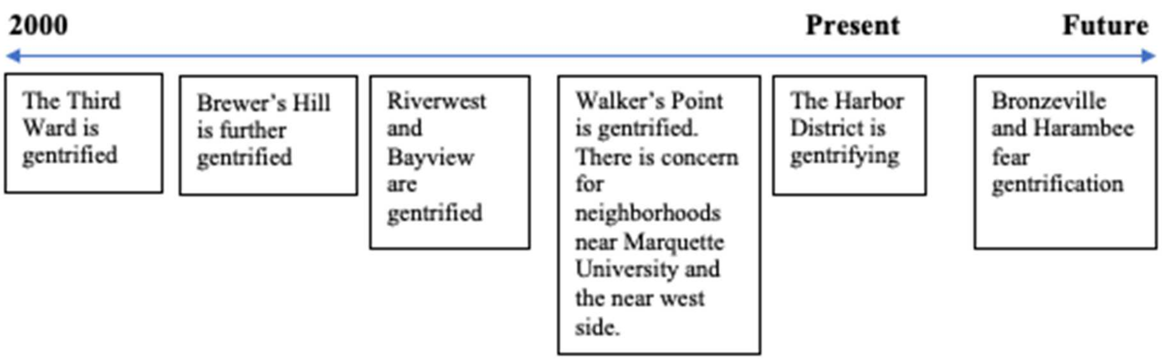
**Note: Integrated block groups are block groups where no racial group comprises more than 49.9% of the total population.*

Data Sources and Variables

The variable for analysis 1, the extent of gentrification in Milwaukee, is a categorical measurement of gentrification. The measurement was created using the 2010 median income, changes in levels of educational attainment from 2010 to 2018, and changes in median housing value from 2010 to 2018 across Milwaukee tracts and block groups. The data used were from the U.S. Census Bureau 5-year ACS estimates from 2010 and 2018. The first step in creating the categorical measure of gentrification was to establish "gentrifiable" neighborhoods: neighborhoods in which the 2010 median income and 2010 median housing value were below the 40th percentile across Milwaukee tracts and block groups. The second step was to determine which of these "gentrifiable" neighborhoods gentrified by 2018: gentrified neighborhoods must have had increases in educational attainment above the 66th percentile across Milwaukee neighborhoods and their median housing values must have increased from 2010 to 2018. The categorical measure of gentrification thus included three categories: gentrifiable/gentrified, gentrifiable/did not gentrify, and not gentrifiable.[9] This operational definition was successfully used by Michael Maciag for his 2015 *Governing* analysis.

These categorizations were then cross-referenced using a simple content analysis which assessed news reports and scholarly articles about Milwaukee gentrification. The simple content analysis was performed using both the UW-Milwaukee Library database and the Google search engine. I used the following keywords: Milwaukee gentrify/gentrified/gentrification and Milwaukee neighborhood revitalization. A timeline of gentrification in Milwaukee was then created (Figure 1) and the quantitative measure of gentrification was assessed for validity. This methodology was inspired by the work done by Barton (2016) on gentrification and crime in New York City.

Figure 1. Timeline of Gentrification in Milwaukee



For the second analysis, it was necessary to collect data on crime and various neighborhood change factors. Crime data for analysis 2 were collected from WIBRS from 2010 and 2018. According to the Milwaukee Police Department, crime against property include theft,

[9] Though neighborhoods may not be considered gentrifiable, this does not necessarily indicate that these neighborhoods are affluent. Being "not gentrifiable" only means that they were more affluent than bottom 39% of Milwaukee neighborhoods.

auto theft, robbery, criminal damage, burglary, locked vehicle, and arson. Crime against persons include homicide and assault.[10] For ease, I refer to crime against property as property crime and crime against persons as violent crime. There were numerous incidents that were coded as multiple crime types. The incident was only counted once to calculate property crime rate *or* violent crime rate if it was coded as more than one crime type of the same kind (property or violent crime; e.g. theft and robbery, or homicide and assault). The incident was counted to calculate *both* property crime rate and violent crime rate if it was coded as more than one crime type of each kind (property and violent crime; e.g. theft and homicide, or criminal damage and assault). Of the 47,015 total reported crimes in 2010, there were 1,052 incidents (2.24%) that were counted towards both property crime rate and violent crime rate. Of the 35,044 number of total reported crimes in 2018, there were 929 incidents (2.65%) that were counted towards both property crime rate and violent crime rate. The crime data were reported by WIBRS using addresses; it was aggregated to the tract and block group levels of analysis with ArcGIS by using census tract and block group shapefiles, geocoding the addresses, and creating a sum of the total number of crimes in each tract and block group.[11] Rates per 10,000 population were calculated for census tracts for both property crime and violent crime. Rates per 1,000 population were calculated for block groups for both property crime and violent crime. This resulted in eight total crime rates. Each of the 2010 and 2018 crime rates were logged and the change in logged crime rates from 2010 to 2018 was calculated.[12]

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[10] Sexual assault is also considered a crime against persons by the Milwaukee Police Department, but was excluded from this analysis because no location data was provided for these incidents.

[11] Due to missing location data, some of the incidents could not be geocoded and included in the sums. This included 0.010% of the 2010 property crimes, 0.003% of the 2010 violent crimes, 0.003% of the 2018 property crimes, and 0.007% of the 2018 violent crimes.

[12] For example, changes in the property crime rate per 1,000 population was found by calculating [logged property crime rate per 1,000 population (2018)] - [logged property crime rate per 1,000 population (2010)].

Thirteen neighborhood change indicators were included as variables in analysis 2. These variables included: changes in residential stability, the percentage the population that is foreign-born, the unemployment percentage, the ratio of racial groups, the percentage of the population that are young males, the population per square mile, median household income, median assessed housing value, the percentage of the population with at least a Bachelor's degree, the percentage of the housing that is unoccupied, the percentage of the population that is "elderly", the percentage of households that are female-headed, and the percentage of the population that is divorced. Residential stability was measured as the percentage of housing units that are renter-occupied. The foreign-born population was measured as the percentage of the population that was born outside of the United States. Unemployment was measured as the percentage of the population that is 16 years and older and is unemployed. Racial distribution was included in the analysis using Blau's Heterogeneity Index.[13] The young male population was measured as the percentage of the population that is male and between the ages of 18 and 24 years old. Population density was calculated by dividing the total tract or block group population by the corresponding tract's or block group's land area (in miles). Income and housing value were measured as the median income and median assessed housing value of the neighborhood. Educational attainment was measured as the percentage of the population that is 25 years and over with a Bachelor's Degree or higher. Unoccupied housing was measured using the percentage of tract/block group housing that is vacant. The elderly population was measured as the percentage of the population of the tract or block group that is 60 years or older. The

[13] Blau's Heterogeneity Index was calculated using the formula [1- sum of squared proportions for each racial group] (Rushton, 2008). The U.S. Census Bureau has six racial groups: White alone, Asian alone, Black alone, Native American/Alaska native alone, Hawaiian/Pacific Islander alone, Other race alone, and Bi or Multiracial. I also included an additional measure that calculated racial distribution as the percentage of the population that is White alone.

percentage of female-headed households was measured as the percentage of family households that are headed by single females. Divorce rate was measured as the percentage of the population that is 15 years and older and divorced. All contextual data came from the 2010 and 2018 ACS 5-year estimates from either the U.S. Census Bureau or IPUMS. Before including this data in the regression models, the data for the these thirteen variables was logged. After logging, the difference in logged values from 2010 to 2018 was calculated; these differences are the variables used in the models for analysis 2.[14]

Statistical Methodology

To examine whether there is a presence or absence of gentrification across Milwaukee census tracts and block groups, a frequency analysis was performed. After calculating which tracts and block groups were not gentrifiable, gentrifiable but did not gentrify, and gentrifiable and gentrified, two frequency tables were constructed (one for tracts and one for block groups).

To test the effects of gentrification (if present) and neighborhood change factors on changes in property crime rate and violent crime rate across Milwaukee census tracts and block groups, a series of linear multiple regression analyses will be utilized (Analysis 2). As the units of analyses are both small and located next to each other, spatial autocorrelation must be accounted for. If there is positive or negative spatial autocorrelation in the data, a spatial error or spatial lag term will be included in the multiple regression model depending on which is more appropriate.

RESULTS

Analysis 1

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[14] As both the independent and dependent variables are calculated as the differences between two logs, the interpretations will examine the change in the predicted ratio of 2018 to 2010 property and violent crime rates. This is because $\log A - \log B$ is equivalent to $\log(A/B)$.

First, analysis 1 examined whether there was gentrification across Milwaukee census tracts and block groups. Using the operational definition described above, there were very few tracts that gentrified from 2010 to 2018 (n= 2), as well as very few block groups that gentrified from 2010 to 2018 (n = 2). These results are mapped in Figure 2 (for census tracts; p. 27) and Figure 3 (for block groups; p. 28). Of the 71 (28.86%) gentrifiable census tracts, two (2.82%) of those census tracts gentrified. Of the 159 (25.77%) gentrifiable block groups, two (1.26%) of those block groups gentrified. By far, the most frequent category was "not gentrifiable" meaning that most census tracts and block groups were not considered gentrifiable in 2010 and 2018 or were considered not considered gentrifiable in 2010 but were considered gentrifiable in 2018. 175 (71.14%) of the census tracts were not gentrifiable and 458 (74.23%) of the block groups were not gentrifiable.

According to the frequency of gentrified neighborhoods across both census tracts and block groups, gentrification from 2010 to 2018 was not very prevalent in Milwaukee. This lack of gentrification aligns with previous results from quantitative analyses of gentrification in other American cities of varying sizes (Hwang & Sampson, 2014; Hwang, 2015; Landis 2015; Maciag, 2015b; Zuk, Bierbaum, Chapple, Gorska, Loukaitou-Sideris, Ong & Thomas, 2015; Timberlake & Johns-Wolfe, 2017).

The gentrified census tracts and block groups are located in the same two neighborhoods of Milwaukee: Riverwest and Walker's Point. Based on the timeline of gentrification in Milwaukee (see Figure 1, p. 20) that was created using a simple content analysis, the quantitative operational definition of gentrification is accurate. Additionally, it is interesting that of the two census tracts that were considered gentrified, there was only one block group that was considered gentrified. By using a smaller aggregation (block group), it is made clear that the characteristics of the smaller land area affected the results at a larger unit of aggregation (census tract). More details on the differences in aggregation will be parsed through later in the analysis.

Table 3. Frequency of levels of gentrification across census tracts and block groups

Unit of analysis	Not gentrifiable	Did not gentrify	Gentrified
Census tracts	175	69	2
Block groups	458	157	2

Preliminary Evaluations for Analysis 2

Analysis 2 tested the relationship between neighborhood change and crime, but gentrification was excluded due to the lack of variation found in analysis 1. Based on predominant criminological theories, various measures of neighborhood change were included in the model. Eight of the thirteen variables are highlighted in social disorganization theory: median income, median housing value, educational attainment, residential mobility (measured using two variables: renter population and vacant housing), foreign-born population, unemployment, and racial composition. Routine activities theory also guided the choice of three variables: young male population, elderly population, and population density; a larger young male population, larger elderly population, and higher population density provides more likely offenders (young males), suitable targets (elderly people), and capable guardians (because of increased population density). In addition, based on research examining the effects of family disruption and crime, two additional variables were included: 1) percent of female-headed households with minor children (Roncek et al., 1981; Immergluck & Smith, 2006), and 2) divorce rate (Immergluck & Smith, 2006).

Though the variables are logged for the regression models, it is more logical and useful for the descriptive statistics to be reported using the unlogged rates and percentages; the descriptive statistics were calculating using the changes in the unlogged rates of each variable

Figure 2. Map of gentrification across Milwaukee census tracts from 2010 to 2018.

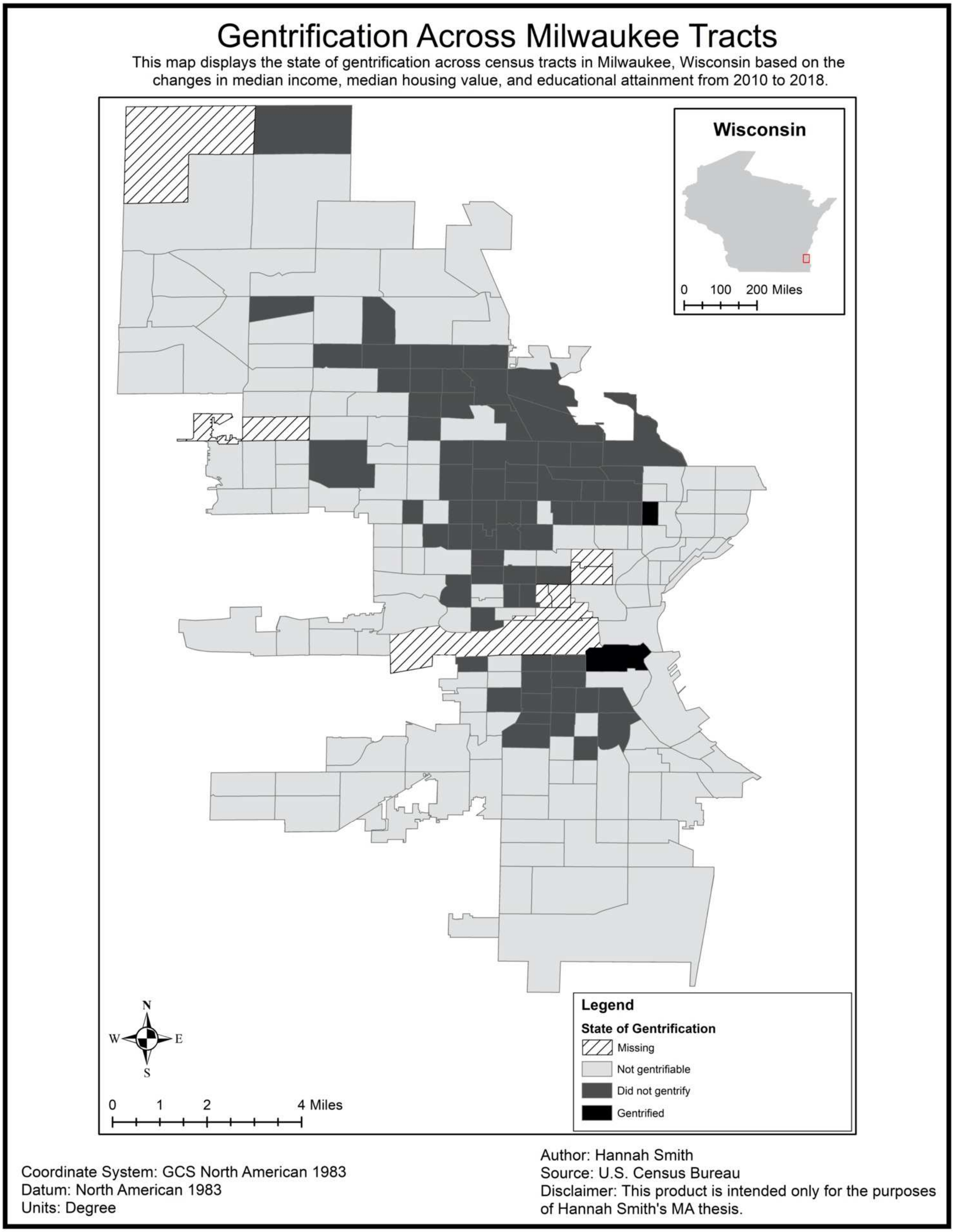

Figure 3. Map of gentrification across Milwaukee block groups from 2010 to 2018.

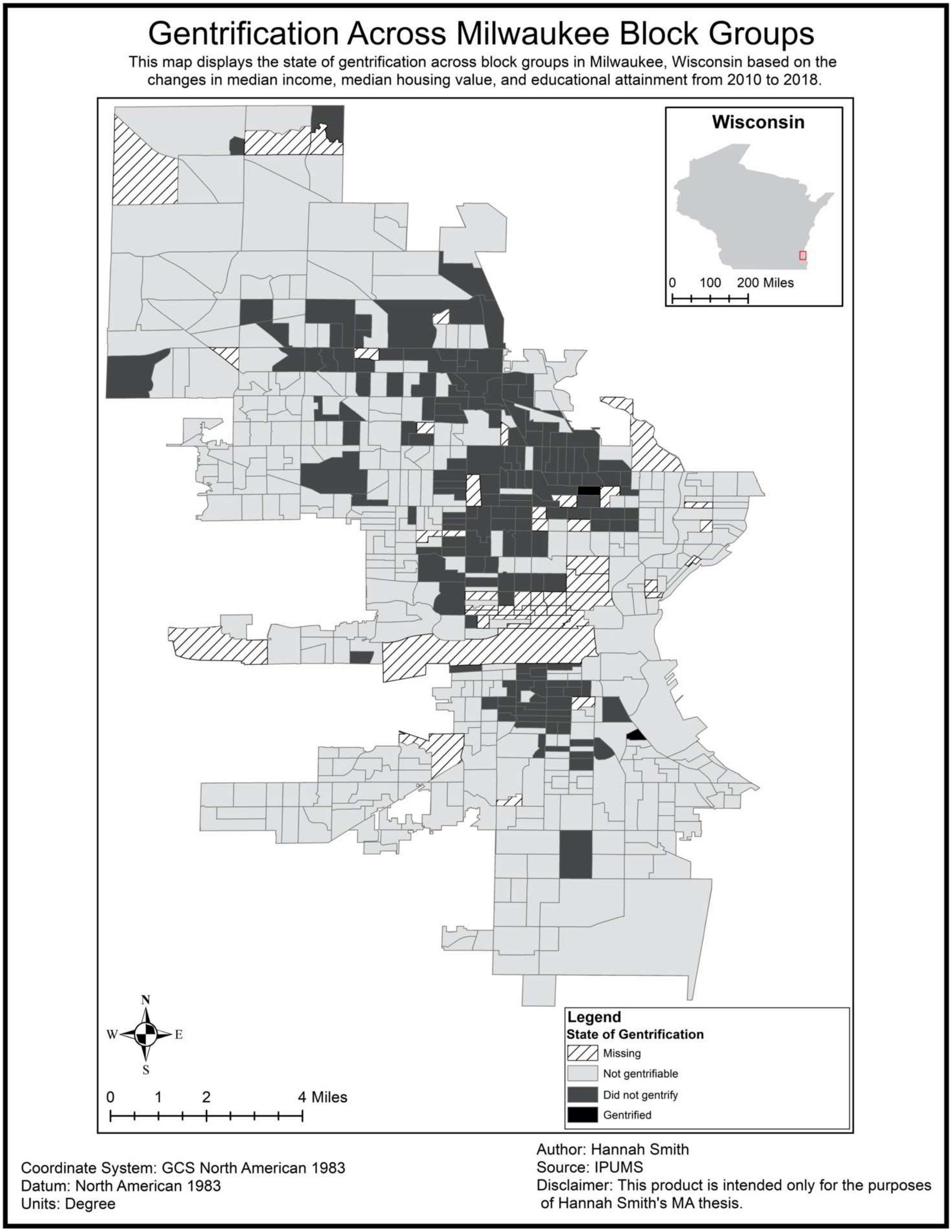

Table 4. Descriptive statistics at the census tract unit of analysis, calculated using the differences from 2010 to 2018 (n= 247)

Variable	Min.	Max.	Mean	Std Deviation
Blau's Heterogeneity Index	-0.244	0.370	0.030	0.106
Unemployment	-43.100	17.400	-3.875	7.005
Young male population	-28.700	25.900	-0.809	6.314
Density	-6429.410	4338.460	-104.941	1522.767
Foreign-born population	-18.952	30.038	0.458	5.225
Renter population	-21.157	27.727	4.670	8.090
Vacant housing	-17.383	19.149	0.381	5.867
Educational attainment	-18.439	37.922	3.022	6.934
Housing value	-146900.000	135500.000	-20520.648	24306.067
Median income	-25737.000	46903.000	4770.780	8763.375
Elderly population	-7.977	15.447	2.593	4.200
Female-headed households	-28.675	23.367	-0.321	7.343
Divorce rate	-12.854	13.360	0.159	4.233
Property crime rate	-1843.414	470.269	-225.154	255.431
Violent crime rate	-141.690	378.127	63.231	79.983

Table 5. Descriptive statistics at the block group unit of analysis, calculated using the differences from 2010 to 2018 (n= 592)

Variable	Min.	Max.	Mean	Std Deviation
Blau's Heterogeneity Index	-0.512	0.640	0.027	0.164
Unemployment	-82.380	12.112	-18.936	12.571
Young male population	-29.517	16.705	-0.447	5.037
Density	-17688.899	11844.078	-149.287	3130.417
Foreign-born population	-36.513	31.507	0.247	8.132
Renter population	-36.947	47.128	4.818	13.352
Vacant housing	-34.124	38.196	0.472	10.363
Educational attainment	-34.173	63.118	3.165	10.701
Housing value	-155500.000	299500.000	-21135.761	31787.570
Median income	-32238.000	123517.000	5491.456	14642.834
Elderly population	-23.369	38.460	2.617	7.859
Female-headed households	-57.350	43.833	-0.398	12.908
Divorce rate	-23.943	25.813	0.004	7.271
Property crime rate	-321.101	59.395	-23.550	29.409
Violent crime rate	-57.789	69.649	6.614	12.731

from 2010 to 2018 (e.g. unlogged percentage of young males in 2018 – unlogged percentage of young males in 2010). The descriptive statistics for the neighborhood change variables are shown in Table 4 (census tracts; p. 29) and Table 5 (block groups; p. 29). Descriptive statistics for the rates and percentages in 2010 and 2018 (*not* the differences from 2010 to 2018) are in Appendix A.

Before performing the regression analyses, diagnostic tests for multicollinearity (see Appendix B) and spatial autocorrelation (see Appendix C) were conducted. Multicollinearity was deemed unlikely, as the strongest correlation between two independent variables in the dataset was between population density and the percentage of the population that is elderly ($r = -0.338$ at the census tract unit of analysis, $r = -0.353$ at the block group unit of analysis).[15]

To investigate the presence of spatial autocorrelation in the data, the Moran's I test was used (see Appendix C). Moran's I measures whether or not there is significant spatial autocorrelation and whether this is positive (clustering of like values) or negative (inverse clustering of values). Although the values of Moran's I were positive for the census tract models, the values were insignificant for the census tract/property crime rate model (Model 1; Moran's I= 0.049, $p = 0.074$) and census tract/violent crime rate model (Model 2; Moran's I= 0.032, $p = 0.152$) meaning that spatial autocorrelation was unlikely among census tracts. However, Moran's I was positive *and* significant for the block group/property crime rate model (Model 3; Moran's I= 0.096, $p < 0.001$) and the block group/violent crime rate model (Model 4; Moran's I= 0.063, $p = 0.008$). This indicates that there was significant and positive spatial autocorrelation among block groups so there was clustering of like values.[16]

[15] The lack of multicollinearity remained the same when the percentage White racial distribution measure was substituted for Blau's Heterogeneity Index. Results available upon request.
[16] The direction and significance of the spatial autocorrelation remained the same when the percentage White racial distribution measure was substituted for Blau's Heterogeneity Index. Results available upon request.

To determine the appropriateness of a spatial lag or spatial error model for Models 3 and 4, further spatial autocorrelation diagnostics were performed (See Appendix C). Kreager et al. (2011) explain the difference between issues of spatial lag and spatial error: "Spatial lag occurs when observations in one neighborhood are dependent upon observations in surrounding neighborhoods. Spatial error occurs when the error terms among the adjacent neighborhoods are correlated due to unobserved heterogeneity." Based on the greater significance of the Lagrange-multiplier lag term (16.177, $p < 0.001$) and the Robust Lagrange-multiplier lag term (7.508, $p = 0.006$) for Model 3 (block groups/property crime rate), a spatial lag model was utilized. Due to the greater significance of the Lagrange-multiplier error term (5.35, $p = 0.020$) and the Robust Lagrange-multiplier error term (5.161, $p = 0.023$) for Model 4 (block groups/violent crime rate), a spatial error model was used. These results suggest that there is a more severe issue with spatial lag in the model for block groups/property crime rate and a more severe issue with spatial error in the model for block groups/violent crime rate.[17]

Regression Models for Analysis 2

To begin the regression analyses, I will first examine the OLS regression models. OLS regression was more appropriate for tract-level analyses due to the lack of spatial autocorrelation. Table 6 (p. 33) shows the results for property crime rate (Model 1) and violent crime rate (Model 2). Looking at model fit, both Model 1 and Model 2 have low R^2 values (R^2 for Model 1 is 0.156 and R^2 for Model 2 is 0.082; See Table 6, p. 33), which indicate that the neighborhood change characteristics only explain 15.6% of the variance in changes in the property crime rate

[17] The spatial lag was also more problematic for Model 3 and the spatial error was also more problematic for Model 4 when the percentage White racial distribution measure was substituted for Blau's Heterogeneity Index. Results available upon request.

and only 8.2% of the variance in changes in the violent crime rate.[18] These indicators of model fit suggest that important explanatory variables are missing from the models and that neighborhood *change* may not be very predictive of changes in crime (even though neighborhood characteristics are strong predictors of neighborhood crime when measured at a single time point; Roncek et al., 1981; McNulty & Holloway, 2000; Morenoff et al., 2001; Immergluck & Smith, 2006, Griffiths & Tita, 2009). This lack of fitness in both Models 1 and 2 is reflected in the lack of statistical significance for most independent variables (See Table 6, p. 33).

Table 6. Models 1 and 2 (OLS regression models, census tract unit of analysis, n= 246)

	Model 1	Model 2
Variable	b	b
Blau's Heterogeneity Index	0.002 (0.037)	-0.007 (0.053)
Unemployment	-0.015 (0.027)	b < 0.001 (0.039)
Young male population	-0.028 (0.032)	0.027 (0.045)
Density	-0.748 (0.159)***	-0.139 (0.227)
Foreign-born population	-0.019 (.0.024)	-0.059 (0.034)*
Renter population	-0.114 (0.090)	0.389 (0.128)**
Vacant housing	-0.054 (.0.028)*	0.004 (0.040)
Educational attainment	-0.058 (0.040)	0.008 (0.057)
Housing value	0.248 (0.097)**	-0.151 (0.139)
Median income	0.086 (0.108)	0.057 (0.154)
Elderly population	-0.076 (0.053)	0.147 (0.075)*
Female-headed households	-0.068 (0.045)	-0.027 (0.064)
Divorce rate	0.045 (0.043)	-0.003 (0.061)

*Note: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.001$*
R^2 for model 1: 0.156, R^2 for model 2: 0.08

For Model 1 (for property crime rate), changes in population density and median housing value from 2010 to 2018 both had statistically significant effects on changes in property crime rates from 2010 to 2018 ($p < 0.001$; $p = 0.011$). The change in the percentage of vacant housing

[18] The strength of R^2 increased slightly in each model when the percentage White racial distribution measure was substituted for Blau's Heterogeneity Index. $R^2 = 0.157$ for Model 1 and $R^2 = 0.097$ for Model 2. However, the coefficients for percentage White were not statistically significant in either model. Results available upon request.

from 2010 to 2018 was also close to reaching statistical significance ($p= 0.057$). The change in property crime rate between 2010 and 2018 is multiplied by 0.931[19] as the ratio of population density between 2010 and 2018 is multiplied by 1.10. This means that the predicted ratio of 2018 to 2010 property crime rate decreases 6.9% as the ratio of population density between 2010 and 2018 increases by 10%. This effect size is quite consequential. The change in property crime rate between 2010 and 2018 is multiplied by 1.024[20] as the ratio of median housing value between 2010 and 2018 increases by 10%. Stated differently, the predicted ratio of 2018 to 2010 property crime rate increases 2.4% as the ratio of median housing value between 2010 and 2018 increases by 10%. Though the effect of the change in vacant housing from 2010 and 2018 does not meet a level of traditional statistical significance ($\alpha= 0.05$), the effect is approaching significant ($p = 0.057$), and therefore, will be further evaluated. The change in property crime rate between 2010 and 2018 is multiplied by 0.995[21] as the ratio of vacant housing units between 2010 and 2018 increases by 10%. In other words, the predicted ratio of 2018 to 2010 property crime rate decreases 0.5% as the ratio of vacant housing between 2010 and 2018 increases by 10%.

Both changes in population density and vacant housing have negative coefficients, indicating that the change in property crime is in a more negative direction as the change in population density and vacant housing increases. In a context of increasing property crime, this would suggest a smaller increase in places where population density and vacant housing increased than where these factors stayed the same. In a context of decreasing property crime, this would suggest a greater decrease in places where these factors increased. Either way,

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[19] $e^{b5\log 1.10}= e^{(-0.748)(0.095)}= e^{(-0.071)}= 0.931$

[20] $e^{b10\log 1.10}= e^{(0.248)(0.095)}= e^{(0.024)}= 1.024$

[21] $e^{b8\log 1.10}= e^{(-0.054)(0.095)}= e^{(-0.005)}= 0.995$

increasing population density[22] and vacant housing would be "good" for crime. Conversely, the change in median housing value has a positive coefficient. This means that as median housing value increases, property crime changes in a more positive direction. Increases in median housing value would be associated with larger increases in property crime in tracts with increasing property crime. Similarly, increases in median housing value would be linked to smaller decreases in property crime in tracts with decreasing property crime. Overall, rising property values are not necessarily beneficial for neighborhood safety.

For Model 2, the only statistically significant variable at the traditional $\alpha= 0.05$ cut-off was the change in the percentage of renters from 2010 to 2018 ($p= 0.003$). However, the change in the percentage of elderly residents and the change in the percent of foreign-born residents were below the less traditional $\alpha= 0.10$ cut-off ($p= 0.052$; $p= 0.091$). The change in violent crime rate between 2010 and 2018 is multiplied by 1.038[23] as the ratio of the percentage of renters between 2010 and 2018 increases by 10%. Put another way, the predicted ratio of 2018 to 2010 violent crime rate increases 3.8% as the ratio of the percentage of renters between 2010 and 2018 increases by 10%. The change in violent crime rate between 2010 and 2018 is multiplied by 1.014[24] as the change in the percentage of the elderly population between 2010 and 2018 increases by 10%. To restate, the predicted ratio of 2018 to 2010 violent crime rate increases 1.4% as the ratio of the percentage of elderly residents between 2010 and 2018 increases by 10%. The change in violent crime rate between 2010 and 2018 is multiplied by 0.994[25] as the change in the percentage of foreign-born residents between 2010 and 2018 increases by 10%;

[22] Although surprising, this finding aligns with past results (Roncek et al., 1981; Butcher & Piehl, 1998; MacDonald et al., 2007).

[23] $e^{b7\log 1.10}= e^{(0.389)(0.095)}= e^{0.037}= 1.038$

[24] $e^{b12\log 1.10}= e^{(0.147)(0.095)}= e^{0.014}= 1.014$

[25] $E^{b6\log 1.10}=e^{(-0.059)(0.095)}=e^{-0.006}= 0.994$

this means that the predicted ratio of 2018 to 2010 violent crime rate decreases 0.6% as the ratio of the percentage of foreign-born residents increases by 10%. Although the changes in renter, elderly, and foreign-born populations are statistically significant, the 3.8%, 1.4%, and 0.6% shifts in the predicted ratio of 2018 to 2010 violent crime rates are not very large.

The change in the percentage of foreign-born residents has a negative coefficient, meaning that increases in the percentage of foreign-born residents is associated with a more negative change in violent crime rate. In tracts with increasing violent crime, this would mean that there would be a smaller increase in those tracts that also experienced an increase in foreign-born residents. In tracts with decreasing violent crime, this suggests that there is a greater decrease in those tracts that also experienced an increase in foreign-born residents. As both the changes in renter and elderly populations have positive coefficients, increases in both variables are related to more positive changes in violent crime rate. When considering Milwaukee tracts with increasing violent crime rates, there would be larger increases in violent crime rates in tracts experiencing growth in renter and elderly populations. When considering tracts with decreasing violent crime rates, there would be smaller decreases in violent crime rates in tracts that had increases in renter and elderly populations. These results suggest that rising foreign-born populations are associated with lower rates of violent crime and rising renter and elderly populations are associated with higher rates of violent crime.

Spatial regression models are used for the block group-level analyses due to significant spatial autocorrelation. Table 7 (p. 40) shows the results for Model 3 (on property crime rate) and Table 8 (p. 41) shows the results for Model 4 (on violent crime rate). When examining model fit for spatial regression models, R^2 is not useful and there are no exact replacements for R^2. Instead, there are various statistics that compare the spatially regressed models to non-spatially regressed versions of the models to determine if the spatial lag or spatial error parameter improved the model (see Tables 7 and 8, pp. 40-41). For Model 3 (on property crime rate), Rho (ρ= 0.214, p= 0.001) was significant and suggested that the spatial lag did influence the OLS estimates. The Likelihood-ratio (LR) test (LR= 14.419, $p < 0.001$), and the comparison of Akaike Information Criterion (AIC) values for the OLS (AIC= 576.443) and SAR (spatial autoregressive or spatial lag; AIC= 564.024) models show that the SAR model was stronger.[26] However, the results of the Lagrange-multiplier (LM) test (LM= 6.001, p= 0.014) demonstrate that there was residual autocorrelation in the model, meaning that there was autocorrelation remaining in the error terms. Overall, Model 3 is stronger than an OLS model, but could be further improved.[27]

The Lambda in the violent crime rate model (Model 4) indicated that spatial error influences the OLS standard error estimates (λ= 0.133, p= 0.025). The LR test (LR= 4.991, p= 0.025) illustrates that the spatial error term improved the model fit. This claim is further supported by the statistical significance of both the Wald test (Wald= 4.987, p= 0.026) and the Hausman test (Hausman= 25.470, p= 0.030), along with the smaller value of the AIC for the SE (spatial error) model (AIC= 1095.792) compared to the value of the AIC for the OLS model (AIC= 1092.802). Altogether, the fit statistics for Model 4 clearly suggest that the spatial error parameter improved the model.[28]

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[26] When comparing the strengths of the models using AIC values, a smaller value of AIC is indicative of a stronger model (Lee & Ghosh, 2009).
[27] The spatial regression diagnostics were nearly identical for Model 3 when the percentage White racial distribution measure was substituted for Blau's Heterogeneity Index. The results still suggest that the spatial lag parameter improved the model. Similarly to the coefficient for Blau's Heterogeneity Index, the coefficient for the percentage White was insignificant. Results available upon request.
[28] The spatial regression diagnostics were somewhat similar for Model 4 when the percentage White racial distribution measure was substituted for Blau's Heterogeneity Index. Most of the results were nearly identical except that the Hausman test became insignificant (Hausman= 21.007, p= 0.101). Similarly to the coefficient for Blau's Heterogeneity Index, the coefficient for the percentage White was insignificant. Results available upon request.

Due to the nature of spatial lag, "observations in one neighborhood are dependent upon observations in surrounding neighborhoods" (Kreager et al., 2011), regular coefficients are not as useful for interpretation as they are in OLS models. Instead, it is necessary to investigate the average direct effect of each variable ("averaged over all n observations providing a summary measure of the impact arising from changes in the i^{th} observation of variable r"), the average indirect effect of each variable ("a measure of the impact of variable r arising from changes across observations surrounding the i^{th} observation, averaged over all n observations") , and the average total effect of each variable ("average direct effect + average indirect effect") (Spielman, 2015).

Similar to both Models 1 and 2, Models 3 and 4 had few statistically significant variables. In Model 3, the only statistically significant variable was the change in housing value from 2010 to 2018 ($p= 0.002$). However, the change in educational attainment from 2010 to 2018 was below the less traditional cut-off of $\alpha= 0.1$ ($p= 0.079$) so the effect of the change in educational attainment is also evaluated. The ratio of housing value between 2010 and 2018 has an average direct effect of 1.018[29] (an increase of 1.8%), an average indirect effect of 1.005[30] (an increase of 0.5%), and an average total effect of 1.022[31] (an increase of 2.2%) on the predicted ratio of 2018 to 2010 property crime rate when the ratio of housing value between 2010 and 2018 increases by 10%. The ratio of educational attainment between 2010 and 2018 has an average direct effect of 0.997[32] (a decrease of 0.3%), an average indirect effect of 0.999[33] (a decrease of 0.1%), and an average total effect of 0.996[34] (a decrease of 0.4%) on the predicted ratio of 2018 to 2010

29 $e^{de10log1.10}= e^{(0.186)(0.095)}= e^{0.018}= 1.018$
30 $e^{ie10log1.10}= e^{(0.048)(0.095)}= 1.005$
31 $e^{te10log1.10}= e^{(0.234)(0.095)}= e^{0.022}= 1.022$
32 $e^{de9log1.10}= e^{(-0.036)(0.095)}= e^{-0.003}= 0.997$
33 $e^{ie9log1.10}= e^{(-0.009)(0.095)}= e^{-0.0009}= 0.999$
34 $e^{te9log1.10}= e^{(-0.046)(0.095)}= e^{-0.004}= 0.996$

property crime rates when the ratio of educational attainment between 2010 and 2018 increases by 10%.

The change in educational attainment has negative direct, indirect, and total effects, meaning that there is a more negative change in property crime rate as the change in educational attainment increases. In the case of block groups with increasing property crime rates, the negative effects suggest a smaller increase in places where educational attainment increased; due to the spatial lag, this smaller increase in property crime rate would also apply to neighboring block groups to a lesser extent. In the case of block groups with decreasing property crime rate, the negative effects indicate a larger decrease in places where educational attainment increased. Again, due to the spatial lag, this larger decrease in property crime rate would also apply to the neighboring block groups albeit to a lesser degree. On the other hand, the change in median housing value has positive direct, indirect, and total effects. For block groups with increasing property crime rate, the positive effects correlate to a larger increase in neighborhoods where median housing value also increased. For block groups with decreasing property crime rate, the positive effects suggest a smaller decrease in block groups where median housing value grew. The positive effects of median housing value also influence neighboring block groups. All in all, higher educational attainment is associated with fewer property crimes and higher median housing value is associated with higher rates of property crime. However, neither of the two variables discussed above- though statistically significant- have effect sizes (the largest of which is 2.2%) that could be considered meaningful.

In Model 4, the only two statistically significant variables were the changes in population density and the renter population from 2010 to 2018 ($p < 0.001$; $p = 0.022$). The interpretations of the coefficients in spatial error models are the same as in OLS models as the spatial error only influences the standard error estimates (Anselin, 2003; Fischer & Wang, 2011; Golgher & Voss, 2016). The change in violent crime rate between 2010 and 2018 is multiplied by 0.942[35] as the ratio of the population density between 2010 and 2018 increases by 10%. Put more naturally, the predicted ratio of 2018 to 2010 violent crime rate decreases 5.8% as the ratio of the population density between 2010 and 2018 increases by 10%. This 5.8% change is quite large. The predicted ratio of violent crime rate from 2010 to 2018 is multiplied by 1.011[36] as the ratio of the percentage of renters from 2010 to 2018 increases by 10%. In other words, the predicted ratio of 2018 to 2010 violent crime rate increases 1.1% as the ratio of the renter population from 2010 to 2018 increases by 10%. Though this 1.1% increase has statistical significance, the size of the effect is not of immense consequence.

The change in population density had an inverse effect on violent crime rates, which suggests that the change in violent crime rate is more negative when the change in population density increases at the block group unit of analysis. Neighborhoods with increasing violent crime rates would experience smaller increases when these neighborhoods also experienced a rise in population density. Likewise, neighborhoods with decreasing violent crime rates would undergo greater decreases when these neighborhoods also had an increase in population density. This finding is similar to that resulting from Model 1 in that it appears that rising population density depresses crime. On the contrary, the change in the renter population has a positive coefficient, meaning that as the change in the renter population increases, there is a positive effect on the change in violent crime rate. Block groups with increasing violent crime rates would experience larger increases when these block groups also experienced a growth in the renter population. Similarly, block groups with decreasing violent crime rates would have

35 $e^{b5\log 1.10} = e^{(-0.630)(0.095)} = e^{-0.060} = 0.942$

36 $e^{b7\log 1.10} = e^{(0.116)(0.095)} = e^{0.011} = 1.011$

smaller decreases where there was also a rise in the percentage of renters. This finding aligns with Model 2 in that renter populations and violent crime rate are positively associated.

DISCUSSION AND CONCLUSION

There are many layers to the above results, making it necessary to summarize. First, based on the results from analysis 1, it is clear that there has been a lack of gentrification taking place in Milwaukee. The operational definition used in this paper deemed certain neighborhoods "gentrifiable"[37] and then determined if these neighborhoods gentrified.[38] From this measure, there were two census tracts and two block groups that were identified as having gentrified in Milwaukee from 2010 to 2018. This was validated using the results from the simple content analysis (see Figure 1, p. 20). These findings support past quantitative research that has demonstrated that gentrification is relatively scant (Hwang & Sampson, 2014; Hwang, 2015; Landis, 2015; Maciag, 2015b; Brown-Saracino, 2017; Timberlake & Johns-Wolfe, 2017; Zuk et al., 2015).

The second major result is that very few neighborhood change characteristics had a significant effect on the change in crime rates from 2010 to 2018. These effects also varied depending on the unit of analysis and the type of crime. At the tract level, changes in population density, median housing value, and vacant housing were found to impact property crime rates, whereas, changes in the renter, elderly, and foreign-born populations were found to be associated with violent crime rates. At the block group level, changes in median housing value and educational attainment were significantly associated with property crime rates, whereas, population density and renter populations both had significant effects on the change in violent crime rate. The two

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[37] Neighborhoods that were below the 40th percentile for median housing value and median income in 2010.
[38] Gentrifiable neighborhoods that were above the 66th percentile for changes in educational attainment from 2010 to 2018 and had an increase in median housing value from 2010 to 2018.

Table 7. Model 3 (SAR regression model, block group unit of analysis, property crime rate as dependent variable, n= 592)

Variable	Direct (S.E.)	Indirect (S.E.)	Total (S.E.)
Blau's Heterogeneity Index	0.025 (0.017)	0.006 (0.005)	0.031 (0.022)
Unemployment	-0.011 (0.017)	-0.003 (0.005)	-0.013 (0.022)
Young male population	0.021 (0.014)	0.006 (0.004)	0.027 (0.018)
Density	-0.018 (0.065)	-0.005 (0.018)	-0.023 (0.083)
Foreign-born population	<0.001 (0.015)	<0.001 (0.004)	<0.001 (0.019)
Renter population	-0.056 (0.032)	-0.015 (0.010)	-0.071 (0.041)
Vacant housing	-0.016 (0.012)	-0.004 (0.003)	-0.02 (0.015)
Educational attainment	-0.036 (0.021)*	-0.009 (0.006)	-0.046 (0.027)*
Housing value	0.186 (0.060)**	0.048 (0.021)**	0.234 (0.076)**
Median income	0.085 (0.050)	0.022 (0.015)	0.107 (0.063)
Elderly population	-0.044 (0.029)	-0.012 (0.009)	-0.056 (0.037)
Female-headed households	0.003 (0.0190	<0.001 (0.005)	0.004 (0.025)
Divorce rate	0.01 (0.020)	0.003 (0.006)	0.013 (0.026)

*Note: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.001$*
Rho[39]= 0.214
LR[40]= 14.419, p= 0.001
LM[41]= 6.001, p= 0.014
AIC (OLS)[42]= 576.443
AIC (SLM)[43]= 564.024

[39] The spatial autoregressive parameter (Anselin, 2003)
[40] Likelihood-ratio test, tests whether the spatial lag term improved the model (Spielman, 2015)
[41] Lagrange-multiplier test, tests for residual autocorrelation (Spielman, 2015)
[42] Akaike Information Criterion for OLS regression model, used to test the fit of the spatial lag model versus the OLS model (Lee & Ghosh, 2009)
[43] Akaike Information Criterion for spatial lag regression model, used to test the fit of the spatial lag model versus the OLS model (Lee & Ghosh, 2009)

Table 8. Model 4 (SE regression model, block group unit of analysis, violent crime rate as dependent variable, n= 592)

Variable	b
Blau's Heterogeneity Index	-0.015 (0.027)
Unemployment	-0.011 (0.027)
Young male population	-0.0003 (0.022)
Density**	-0.63 (0.099)
Foreign-born population	0.017 (0.023)
Renter population*	0.116 (0.051)
Vacant housing	-0.008 (0.018)
Educational attainment	-0.003 (0.033)
Housing value	0.068 (0.093)
Median income	-0.034 (0.078)
Elderly population	0.052 (0.044)
Female-headed households	0.032 (0.029)
Divorce rate	0.008 (0.032)

*Note: * $p < 0.1$ **$p < 0.05$ ***$p < 0.001$*

Lambda[44]= 0.133

LR[45]= 4.991, p= 0.025

Wald[46]= 4.987, p= 0.026

Hausman[47]= 25.470, p= 0.030

AIC (OLS)[48]= 1095.792

AIC (SEM)[49]= 1092.802

[44] The spatial autoregressive parameter (Anselin, 2003)

[45] Likelihood-ratio test, tests whether the spatial error term improved the model (Spielman, 2015)

[46] Tests whether the spatial error term improved the model (Spielman, 2015)

[47] Tests whether or not the spatial error model is better fitting than the OLS model (Pace and LeSage, 2009)

[48] Akaike Information Criterion for OLS regression model, used to test the fit of the spatial error model versus the OLS model (Lee & Ghosh, 2009).

[49] Akaike Information Criterion for spatial error regression model, used to test the fit of the spatial error model versus the OLS model (Lee & Ghosh, 2009).

common variables among these models were that the change in median housing value affected the change in property crime rate and the change in renter populations affected the change in violent crime rate. Despite the statistical significance of certain variables, very few of the variables mentioned had effect sizes that could be considered consequential on the changes in property crime or violent crime rates. However, it needs to be reiterated that the OLS models were extremely weak and, though the spatial regression models were better-fitting[50] than the OLS models at the block group unit of analysis, the results obtained from these analyses should still be interpreted with caution.

The direction of the coefficients provide mixed support for the theories discussed earlier in the paper. Social disorganization theory suggests that crime increases as social disorganization increases; social disorganization is exacerbated by disadvantage, residential mobility, and population heterogeneity. While some of the models found support for the relationships proposed by social disorganization theory, other models did the opposite. Models 2 and 4 found that increases in renter populations (a measure of residential mobility) were associated with greater levels of violent crime at the tract and block group units of analysis. However, findings from Model 1 demonstrated that increases in vacant housing (a measure of residential instability) were linked to lower levels of property crime at the tract level. Results from Model 3 indicate that increases in educational attainment (a measure of disadvantage/level of affluence) were associated with lower levels of property crime at the block group unit of analysis. Contrarily, Models 1 and 3 found that increases in median housing value (a different measure of disadvantage/level of affluence) were linked to greater levels of property crime at the tract and block group units of analysis. Finally, Model 2 found that increases in foreign-born population (a

[50] Meaning that the models were better-fitting according to the LR tests, comparison of the AIC values, Hausman test, and Wald test.

measure of population heterogeneity) were associated with lower levels of violent crime at the tract unit of analysis. Though this finding does not align with the originally proposed relationship between foreign-born populations and crime in social disorganization theory, it does support the more recent theory that communities of foreign-born residents actually may promote social organization (Kirk & Laub, 2010; Wang, Zhang & Wu, 2017). Overall, there was contradictory evidence for social disorganization theory.

The findings across three of the four models were supportive of routine activities theory. Routine activities theory stresses that the following three things are linked to an increased risk of crime: (1) a suitable target, (2) a likely offender, and (3) a lack of capable guardianship. Model 2 found that increases in elderly populations were associated with greater levels of violent crime at the tract level; an increased elderly population would provide both more suitable targets and fewer capable guardians, heightening the risk of crime. Models 1 and 4 demonstrated that increases in population density are related to lower levels of property crime across tracts and block groups. As the population density increases, it is more likely that there will be a greater number of capable guardians which may deter crime.

There are a few other major takeaways from this research. This paper evaluated the differences in two units of analysis for operationalizing neighborhoods: census tracts and block groups. For analysis 1, the prevalence of gentrification across Milwaukee, there were the same number of tracts and block groups that were categorized as having gentrified. The two census tracts and two block groups were overlapping; as stated earlier, by using a smaller aggregation (block group), it is made clear that the characteristics of the smaller land area affected the results at a larger unit of aggregation (census tract). The unit of analysis also affected the methods and results used to answer analysis 2. For the methods of analysis, the units of aggregation differed in their level of spatial autocorrelation and thus the type of regression model necessary to assess the data. There was not evidence of significant spatial autocorrelation at the census tract unit of analysis, but there was evidence of significant spatial autocorrelation at the block group unit of analysis. Lastly, the two units of analysis were further contrasted based on the statistical significance of different coefficients. Though changes in population density and median housing value were both statistically significant at the census tract and block group levels (for changes in violent crime rate and property crime rate, respectively), there were numerous other variables that only had statistically significant effects at either the census tract or block group unit of analysis. However, this variation across models may also be accounted for based on the type of regression model used (an OLS model versus a spatial regression model) and should be explored further in the future.

This paper also investigated the differences between two dependent variables: the change in property crime rate and the change in violent crime rate. As mentioned earlier, the independent variables (neighborhood change characteristics) influenced the two types of crime differently. Whereas changes in population density, housing value, vacant housing, and educational attainment affected the change in property crime rate, changes in population density, renter populations, elderly populations, and foreign-born populations affected the change in violent crime rate. These results mirror the sentiment from previous researchers that it is important to distinguish between different types of crime as the mechanisms underlying the changes in different types of crime vary (Roncek et al., 1981; McDonald, 1986; Krivo & Peterson, 1996; Butcher & Piehl, 1998; McNulty & Holloway, 2000; Santiago et al., 2003; Immergluck & Smith, 2006; Van Wilsem et al., 2006; Lee, 2010; Kreager et al, 2011; Papachristos et al., 2011).

Though useful insights can be procured from the methods used and results found in this paper, there are a few limitations worth expounding upon. First, the only city examined in the analysis is Milwaukee. Though Milwaukee is theoretically interesting in that it is an understudied mid-size U.S. city and there is little quantifiable gentrification relative to major U.S. cities, Milwaukee provides only a small number of gentrified observations at both the census tract and block group units of analysis which inhibits the ability to test the effect of gentrification on changes in crime rates. Other cities similar in stature and prestige to Milwaukee (e.g. St. Louis, Detroit, Indianapolis, etc.) could be added to the analysis in order to evaluate the effect of gentrification on changes in crime rates using regression.

Second, the use of spatial autocorrelation (and thus the need for spatial regression models) prohibited the use of multiple imputation to handle missing data. Instead, listwise deletion had to be used and the neighborhoods with missing data were excluded from the analysis. As discussed in the methods section, kriging could be used in the future to estimate missing values for spatial regression models. This technique is quite advanced and was beyond the scope of this project, but would allow for incomplete observations to be included in the regression models and would be a fruitful undertaking in the future.

Third, along the same line, the spatial regression models used in this paper (the spatial autoregressive/spatial lag model and the spatial error model) may not have been the most advanced/appropriate spatial regression models to perform analysis 2. Other spatial regression models, such as the Spatial Durbin Model or the spatially-lagged X model, may be better suited for this data and could produce more reliable results. These models should be explored in the future and compared to the models generated for this paper.

Finally, the 2010 to 2018 timeframe of this study limited the amount of change that was able to be captured across Milwaukee neighborhoods. Though very few neighborhood change variables from 2010 to 2018 had statistically significant effects on changes in crime, this may not necessarily be the case for these same variables when measured over a longer period of time. Unfortunately, due to both U.S. Census and WIBRS data limitations, the timeframe was constricted in this study. There may be more datasets available in the future that could be used to expand the timeframe in Milwaukee. Future researchers could also perform this study using more temporally expansive data from similar cities.

Despite the limitations and lack of statistically significant findings, analysis 1 offers more awareness of how neighborhoods have been changing over the past decade. Analysis 1 measures the change in the level of neighborhood affluence (median assessed housing value, median income, and educational attainment); having maps that illustrate where there was a rise in affluence may advance Milwaukee's understanding of how to improve neighborhood well-being across the city. Additionally, analysis 2 may provide useful insight into crime trends in the City of Milwaukee. Population density, vacant housing units, a more highly educated population, and more foreign-born residents were "good" for crime, while rises in assessed housing value, a population made up of more renters, and a larger elderly population were "bad" for crime; understanding the reasons behind these findings may aid city officials in making Milwaukee more safe.

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APPENDIX A:

Descriptive Statistics for 2010 and 2018

Table 1. Descriptive statistics at the census tract unit of analysis (2010) (n= 249)

Variable	Min.	Max.	Mean	Standard Deviation
Blau's Heterogeneity Index	0	0.700	0.341	0.187
Unemployment	0	46.900	11.690	8.400
Young male population	0	74.800	12.087	10.813
Density	321.25	31970	8756.389	5617.976
Foreign-born population	0	43.370	8.541	9.442
Renter population	0.680	100	51.130	21.316
Vacant housing	0	36.360	10.314	7.200
Educational attainment	0	81.400	23.701	19.011
Housing value	44600	693700	153477.108	70961.855
Median income	8477	186154	40750.185	19075.450
Elderly population	0	40.870	14.164	7.434
Female-headed households	0	73.150	20.963	14.38
Divorce rate	0.250	21.850	10.509	3.704
Property crime rate	0	3299.110	588.223	470.948
Violent crime rate	0	620.590	131.287	130.331

Table 2. Descriptive statistics at the census tract unit of analysis (2018) (n= 248)

Variable	Min.	Max.	Mean	Standard Deviation
Blau's Heterogeneity Index	0.010	0.720	0.371	0.171
Unemployment	0.100	31.200	7.815	5.619
Young male population	1.800	81.400	11.277	10.935
Density	288.300	29690	8651.448	5241.207
Foreign-born population	0	38.800	8.999	8.444
Renter population	2.810	100	55.800	20.709
Vacant housing	0	36.510	10.696	7.070
Educational attainment	0.450	87.250	26.723	20.828
Housing value	32200	653500	132670.968	79548.292
Median income	8967	160417	45520.965	22279.009
Elderly population	1.180	44.270	16.757	7.314
Female-headed households	0	56.090	20.642	13.390
Divorce rate	0.870	26.320	10.668	3.655
Property crime rate	0	1455.700	363.070	278.737
Violent crime rate	0	698.050	194.518	185.072

Table 3. Descriptive statistics at the block group unit of analysis (2010) (n= 644)

Variable	Min.	Max.	Mean	Standard Deviation
Blau's Heterogeneity Index	0	0.750	0.324	0.203
Unemployment	2.420	82.380	24.109	13.780
Young male population	0	50.590	5.664	6.492
Density	229.790	45828.860	9824.507	6744.766
Foreign-born population	0	59.340	8.617	10.940
Renter population	0	100	49.497	24.470
Vacant housing	0	47.480	10.137	9.554
Educational attainment	0	88.320	21.965	19.165
Housing value	9999	693700	147781.986	69402.295
Median income	7170	186154	40875.92	20118.133
Elderly population	0	61.820	14.372	9.556
Female-headed households	0	81.580	22.031	16.552
Divorce rate	0	32.860	10.868	5.635
Property crime rate	0	660.550	62.038	53.980
Violent crime rate	0	108.630	14.448	15.669

Table 4. Descriptive statistics at the block group unit of analysis (2018) (n= 597)

Variable	Min.	Max.	Mean	Standard Deviation
Blau's Heterogeneity Index	0	0.750	0.352	0.193
Unemployment	0	39.410	5.172	4.612
Young male population	0	44.430	5.217	5.825
Density	286.840	45937.260	9675.220	6300.662
Foreign-born population	0	56.740	8.865	9.799
Renter population	0	100	54.384	23.899
Vacant housing	0	44.880	10.627	8.985
Educational attainment	0	95.430	25.130	21.271
Housing value	22900	696600	127225.361	79326.513
Median income	7872	250001	46923.098	25173.185
Elderly population	0	65.540	16.989	9.611
Female-headed households	0	66.840	21.613	15.596
Divorce rate	0	34.300	10.872	5.706
Property crime rate	0	339.450	38.488	33.629
Violent crime rate	0	97.050	21.061	20.612

APPENDIX B:

Correlation Matrices

Table 1. Correlations between independent variables at the census tract unit of analysis

Variable	Blau's Heterogeneity Index	Unemployment	Young male population	Density	Foreign-born population	Renter population	Vacant housing	Educational attainment	Housing value	Median income	Elderly population	Female-headed households	Divorce rate
Blau's Heterogeneity Index	1	-0.091	-0.11	0.026	0.261	0.092	0.079	-0.076	0.115	0.074	0.012	-0.015	-0.024
Unemployment	-0.091	1	0.173	0.058	-0.144	0.012	-0.103	-0.085	-0.007	-0.023	-0.032	0.161	-0.075
Young male population	-0.11	0.173	1	0.113	-0.111	0.054	-0.031	-0.044	0.022	-0.025	-0.055	0.074	-0.077
Density	0.026	0.058	0.113	1	0.03	0.131	-0.245	-0.141	0.242	0.155	-0.338	0.193	-0.126
Foreign-born population	0.261	-0.144	-0.111	0.03	1	-0.063	-0.024	0.036	-0.109	0.082	0.054	-0.097	-0.033
Renter population	0.092	0.012	0.054	0.131	-0.063	1	-0.097	-0.08	0.001	-0.215	-0.067	0.124	-0.04
Vacant housing	0.079	-0.103	-0.031	-0.245	-0.024	-0.097	1	-0.012	0.036	-0.045	-0.064	0.092	0.062
Educational attainment	-0.076	-0.085	-0.044	-0.141	0.036	-0.08	-0.012	1	0.022	0.091	0.043	-0.109	-0.044
Housing value	0.115	-0.007	0.022	0.242	-0.109	0.001	0.036	0.022	1	0.198	-0.203	-0.008	-0.175
Median income	0.074	-0.023	-0.025	0.155	0.082	-0.215	-0.045	0.091	0.198	1	-0.147	-0.108	-0.067
Elderly population	0.012	-0.032	-0.055	-0.338	0.054	-0.067	-0.064	0.043	-0.203	-0.147	1	-0.149	0.103
Female-headed households	-0.015	0.161	0.074	0.193	-0.097	0.124	0.092	-0.109	-0.008	-0.108	-0.149	1	0.151
Divorce rate	-0.024	-0.075	-0.077	-0.126	-0.033	-0.04	0.062	-0.044	-0.175	-0.067	0.103	0.151	1

Table 2. Correlations between independent variables at the block group unit of analysis

Variable	Blau's Heterogeneity Index	Unemployment	Young male population	Density	Foreign-born population	Renter population	Vacant housing	Educational attainment	Housing value	Median income	Elderly population	Female-headed households	Divorce rate
Blau's Heterogeneity Index	1	-0.008	0.018	0.03	0.182	0.039	0.015	-0.027	0.092	0.019	-0.051	0.043	-0.019
Unemployment	-0.088	1	0.065	0.015	-0.091	-0.054	-0.015	-0.089	-0.009	-0.045	-0.055	0.05	-0.025
Young male population	0.018	0.065	1	0.059	-0.047	0.026	0.009	-0.008	-0.043	0.074	-0.059	0.001	-0.095
Density	0.03	0.015	0.059	1	0.079	0.129	-0.214	-0.082	0.072	0.193	-0.353	0.16	-0.172
Foreign-born population	0.182	-0.091	-0.047	0.079	1	-0.031	0.027	0.038	-0.038	0.036	0.042	-0.084	0.004
Renter population	0.039	-0.054	0.026	0.129	-0.031	1	-0.064	0.012	0.009	-0.115	-0.046	0.001	-0.014
Vacant housing	0.015	-0.015	0.009	-0.214	0.027	-0.064	1	-0.01	-0.012	-0.068	0.054	-0.074	0.038
Educational attainment	-0.027	-0.089	-0.008	-0.082	0.038	0.012	-0.01	1	0.012	0.088	0.001	-0.112	-0.009
Housing value	0.092	-0.009	-0.043	0.072	-0.038	0.009	-0.012	0.012	1	0.126	-0.107	-0.032	-0.015
Median income	0.019	-0.045	0.074	0.193	0.036	-0.115	-0.068	0.088	0.126	1	-0.16	-0.089	-0.081
Elderly population	-0.051	-0.055	-0.059	-0.353	0.042	-0.046	0.054	0.001	-0.107	-0.16	1	-0.154	0.122
Female-headed households	0.043	0.05	0.001	0.16	-0.084	0.001	-0.074	-0.112	-0.032	-0.089	-0.154	1	0.11
Divorce rate	-0.019	-0.025	-0.095	-0.172	0.004	-0.014	0.038	-0.009	-0.015	-0.081	0.122	0.11	1

APPENDIX C:

Spatial Regression Diagnostics

Table 1. Spatial autocorrelation diagnostics by model (Observed Moran's I)

Model	Observed Moran's I	P-value
Census tract/property crime rate (Model 1)	0.049	0.074
Census tract/violent crime rate (Model 2)	0.032	0.152
Block group/property crime rate (Model 3)	0.096	$p < 0.001$
Block group/violent crime rate (Model 4)	0.063	0.008

Table 2. Spatial regression diagnostics for the census tract models (Models 1 and 2)

Model	LM[1]-Error	P-value	LM-Lag	P-value	RLM[2]-Error	P-value	RLM-Lag	P-value
Model 1	1.425	0.233	1.674	0.196	0.003	0.954	0.252	0.616
Model 2	0.614	0.433	0.303	0.582	1.283	0.257	0.973	0.324

[1] LM stands for Lagrange-Multiplier.
[2] RLM stands for Robust Lagrange Multiplier

Table 3. Spatial regression diagnostics for the block group models (Models 3 and 4)

Model	LM[1]-Error	P-value	LM-Lag	P-value	RLM[2]-Error	P-value	RLM-Lag	P-value
Model 3	12.517	$p < 0.001$	16.177	$p < 0.001$	3.847	0.050	7.508	0.006
Model 4	5.350	0.020	3.288	0.070	5.161	0.023	3.098	0.078

[1] LM stands for Lagrange-Multiplier.
[2] RLM stands for Robust Lagrange Multiplier