ABSTRACT

Title of Dissertation:	AN EMPIRICAL TEST OF IMMIGRANT REVITALIZATION: UNVEILING THE CRIME-REDUCING POWER OF IMMIGRANT SOCIAL CAPITAL
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The consensus in the immigration-crime literature is that immigration either has a null or an inverse relationship with neighborhood crime (Ousey & Kubrin, 2018). These findings align with the "immigrant revitalization thesis," which argues that immigration reduces neighborhood crime by producing immigrant social capital and developing community social control. However, the proposed revitalization process has been rarely tested empirically. This dissertation contributes to the current literature by examining the immigration-crime relationship at the neighborhood level and the intervening mechanism of immigration social capital using a large sample of neighborhoods across the U.S. Specifically, it investigates the mediating influence of stable families, multigenerational families, local businesses, and self-employment in the immigration-crime nexus. Using the newly collected National Neighborhood Crime Study 3 Pilot Panel data, I employ a series of fixed-effects and structural equation models (SEM) for violent crime and burglary. The findings highlight the importance of stable families, namely that immigrant neighborhoods bring in stable family structures that translate into less violence in the

neighborhood. However, analyses do not find significant mediating influences for other forms of immigrant social capital. The results provide partial support for the immigrant revitalization perspective and warrant further methodological development and theoretical revision when studying the immigration-neighborhood crime link.

AN EMPIRICAL TEST OF IMMIGRANT REVITALIZATION: UNVEILING THE CRIME-REDUCING POWER OF IMMIGRANT SOCIAL CAPITAL

by

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Chapter 1: Introduction

During the 1990s-2000s, the swelling of immigration in the U.S. led to newfound policy and public concerns around its perceived effects on crime (Camarota, 2011). In response to those concerns, criminologists generated a great body of work showing that immigration either has a null effect or a negative effect on crime (Ousey & Kubrin, 2018). These works argued that immigration might buffer or reduce crime by revitalizing local communities through what the scholars referred to as the "immigrant revitalization perspective" (Feldmeyer et al., 2019; Kubrin & Desmond, 2015; M. T. Lee & Martinez Jr., 2002; Martinez Jr. et al., 2010; Sampson & Bean, 2006; Vélez, 2006). According to this perspective, immigrant communities are places where social organization produce extensive social capital, defined as resources originating from relationships built within social organizations that produce desirable outcomes for all parties involved (Bankston, 2014; Coleman, 1990; Sampson et al., 1999). These strong interpersonal relationships among families, friends, neighbors, and local institutes forge shared social norms and values, mutual trust, and support that facilitates social control within communities. Immigration, by fostering various forms of community social organization that bolster immigrant social capital and community social controls, can thus revitalize and protect neighborhoods from crime (Lee & Martinez, 2002).

Figure 1 provides a visualization of my conceptual framework. Neighborhoods that have relatively large shares of immigrants are places that incubate immigrant social capital and mitigate crime. Three forms of resources

constitute immigrant social capital: obligation and expectation, informational channel, and social norms, which will be further discussed in Chapter 2 (Coleman, 1990; Kao, 2004). I argue family structures and local economy, which contribute to the creation of the three forms of resources mentioned above, are the key players in the making of immigrant social capital. The three resources of immigrant social capital are also the ingredients for communities to develop community social control and keep crime at bay. Essentially social capital encapsulates both the relationships and the action that, by reinforcing social control, bring about reductions in crime. In this dissertation, I operationalize parts of my conceptual framework to explore the mechanisms between immigration and neighborhood crimes. Specifically, I measure immigrant presence, social institutions that bring residents together and stimulate collective action – namely stable family structures and local business infrastructures – and crime at the neighborhood level.

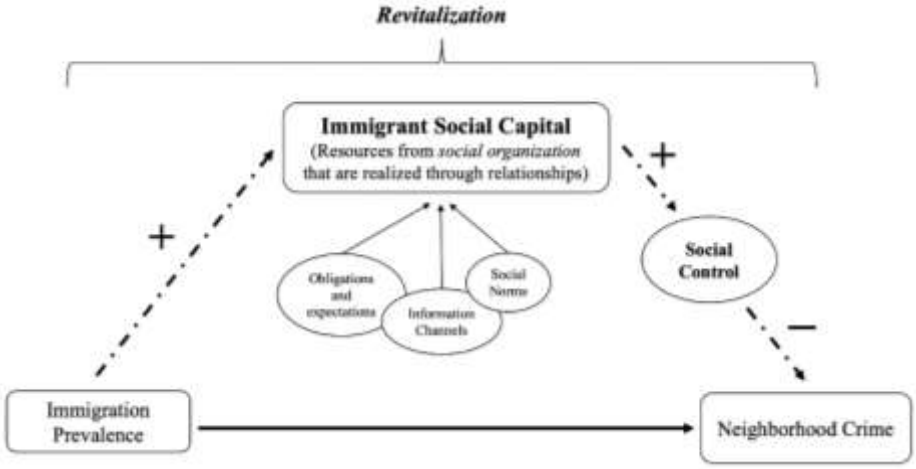

Figure 1. Conceptual Model.
(The conceptual relationship between immigration and crime is based on social disorganization theory and the immigrant revitalization perspective (Burisk & Grasmick, 1993; Hunter, 1985; Kubrin & Desmond, 2015; Feldmeyer et al., 2019; Lee & Martinez, 2002; Martinez et al., 2010; Sampson, Morenoff, and Earls, 1999; Sampson, Raudenbush, & Earls, 1999; Vélez, 2006). The solid line denotes a direct relationship while the dash-dot line denotes an indirect relationship.)

I draw on several key studies to explore how immigrant social capital mediates the immigration-crime relationship, and how this process of revitalization reduces neighborhood crime. Feldmeyer and colleagues (2019) investigate the mediating mechanism of friendship and kinship ties and find that immigrant concentration is linked to stronger social networks that reduce neighborhood violence. On the other hand, Kubrin and Desmond (2015) explore whether immigrant-concentrated neighborhoods produce less crime and delinquency due to the role of community social capital and violent victimization. Contrary to their expectations, both social capital and violent victimization did not mediate the relationship between immigrant concentration and adolescent violence.

Although not at the neighborhood level, Stansfield (2014) examines the mediating role of Hispanic-owned businesses across 131 U.S. cities. He first finds an inverse relationship between immigration and property crime. After including the number of Hispanic-owned businesses in the model, the protective effect of immigration on property crime becomes statistically insignificant, indicating a possible mediating influence. Lastly, a recent work by Ramos and his colleagues (2023) empirically tests the immigrant revitalization perspective using 20 years of data from 139 metropolitan statistical areas. Their investigation shows that immigration reduces violent crime by enhancing local institutions like churches and voluntary organizations. Yet, both local economies and married households do not mediate the relationship as expected. In sum, these studies show that different forms of immigrant social capital play important roles in the way how immigration reduces

crime, but their influences are not always significant, or sometimes even contradict what the theory expects.

Although prior studies contributed to the literature by illuminating the mediating process that links immigration to neighborhood crime, current evidence is limited in three important ways. First, only one study considers the full spectrum of the immigrant revitalization perspective, which indicates immigration revitalizes communities by (1) strengthening social ties among families, friends, and other residents; (2) invigorating local economies; and (3) building stronger community institutions. However, this study only examines immigrant revitalization at the metropolitan level instead of at the neighborhood level where revitalization (e.g., building social ties, sharing information and resources, producing social control, etc.) is hypothesized to occur (Ramos, 2023).

Second, studies that examine immigrant revitalization at the neighborhood level only focus on how family and friendship, one of the community social institutions that produce social control, influence crime. They overlook the nature of immigrant families, specifically the stability and multigenerational character of immigrant families that promote strong social controls, as well as the role immigration plays in creating economic opportunities. Both family structure and economy have theoretical grounds and empirical validity for their contribution to social controls that reduce neighborhood crime.

Finally, the proposed immigrant revitalization process in the established literature has not been tested in a representative sample of neighborhoods across the U.S. For instance, the Feldmeyer et al. (2019) study only investigates neighborhoods

in Chicago. Kubrin and Desmond's (2015) study employs a nationally representative sample of adolescents using the National Longitudinal Study of Adolescent to Adult Health (Add Health), but their school-based sample may not necessarily capture the diverse neighborhoods in the country.

This dissertation addresses these issues and builds on prior research in three key ways. First, to fulfill the prerequisite of mediation analysis, I collect the third wave of the National Neighborhood Crime Study (NNCS3-P), which is a panel dataset consisting of a sample of neighborhoods across 18 cities for the past two decades (circa 2000, 2010, 2020, that allows me to examine the immigration-crime relationship at the neighborhood level, specifically the census tract level. Second, I consider the various ways in which immigration revitalizes communities, including stable family structures and the local economy, and how it affects neighborhood crime. While most studies mentioned above only look at violent crime, this study examines both violent crime and property crime at the neighborhood level. Lastly, there are somewhat mixed findings in the existing literature that the proposed revitalization process does not significantly mediate the immigration-crime relationship and may even operate in the opposite direction of what the perspective expects. Hence, this study contributes to the literature by developing an empirical basis to understand the complex relationship between immigration and neighborhood crime.

The goal of this dissertation is to empirically examine the nature of immigrant social capital as the intervening mechanism between immigration and neighborhood crime. I focus on two aspects of how immigration revitalizes communities and

potentially controls neighborhood crime. My aim in this dissertation is to investigate (1) the state of the immigration-crime relationship at the neighborhood level, and whether immigrant social capital, in the form of (2) family structure and (3) local economy, is a mechanism by which immigration influences neighborhood crime. In this dissertation, I seek to shed light on the relationship between immigration and neighborhood crime over the past twenty years, and whether certain sources of immigrant social capital – such as the prevalence of stable and multigenerational family structures, as well as local businesses and ethnic entrepreneurship – mediate the influence of immigration on neighborhood crime.

In Chapter 2 of this dissertation, I review the status of the immigration-crime literature and conceptual arguments that explain the relationship, with a special focus on the immigrant revitalization perspective and how immigration brings about immigrant social capital (as shown in Figure 1). In Chapter 3, I describe the original NNCS study and the newly collected NNCS3-P along with the operationalization of measures used. Additionally, I detail the analytical plan for conducting mediation analysis using structural equation modeling to answer the research questions. In Chapter 4, I present a descriptive picture of the neighborhoods in the sample and the results of the mediation analyses. I find partial support for the immigrant revitalization perspective whereby immigrant-populated neighborhoods have less violence because of the benefits of having more stable families. In Chapter 5, I conclude the findings with a discussion of limitations, implications, and suggestions for future research.

Chapter 2: Literature Review

The Immigration-Crime Relationship

I. The Current State of the Immigration-Crime Relationship

In recent decades, crime in the U.S. has decreased. According to the Uniform Crime Report (UCR), the violent crime rate fell from about 500 per 100,000 people in 2000 to less than 400 per 100,000 in 2021 (about a 20% decline), and from about 3,600 per 100,000 to 1,800 per 100,000 (about a 50% decline) for the property crime rate. At the same time, immigration has increased. Specifically, immigrants as a share of the national population have increased from 11% to about 15% over the past 20 years, and the Census Bureau has projected that 17% of the U.S. population will be foreign-born by 2060. These descriptive trends suggest immigration and crime are inversely related. However, further examination is needed to empirically assess the immigration-crime relationship.

Empirical examinations of immigration and crime show that immigration either has a null effect on crime or is inversely related to neighborhood crime (Ousey & Kubrin, 2018). In their meta-analysis of 51 published immigration-crime studies published between 1994 and 2014, Ousey and Kubrin (2018) show that the most common outcome in prior studies is the null effect of immigration on crime, with 62% of the effect-size estimates being not significant. Although less common than the null findings, the majority of the statistically significant relationships are negative, meaning immigration is associated with less crime.

While some might argue the null and negative relationships tell substantively different stories, the null findings may still show support for the “negative” story

of the immigration-crime relationship. Although Ousey and Kubrin (2018) found that immigration mostly has a null effect on crime, they find in their meta-analysis that the associations of the null relationships are generally negative. They suggest that most of the time the effect size is too weak to infer an inverse relationship between immigration and crime. Thus, it is naïve to conclude that immigration does not influence crime, especially when there is a significant immigration-crime association (which is usually negative). In sum, both descriptive and empirical evidence from a large body of studies show that immigration is most likely to be associated with less crime.

In general, Ousey and Kubrin's meta-analyses demonstrate that the observed findings hold up regardless of how immigration and crime are measured (single crime type, index of total, violent, or property crime), the unit of analysis (census tracts/census blocks/neighborhood clusters or cities/counties/MSA), and study design (cross-sectional or longitudinal). Nonetheless, there are variations in the immigration-crime relationship across study designs. For instance, while there is no significant variation in the immigration-crime relationship among studies using different measures of immigration, the relationship varies when using different measures of crime. Immigration significantly reduces homicide as a single crime measure while immigration increases crimes when captured as the total crime index, and property crime index (Ousey & Kubrin, 2018). Other measures of crime are mostly negative but not statistically significant. However, there are no significant differences in the mean effect sizes among different crime measurements. In terms of the unit of analysis, the immigration and crime

relationship at the neighborhood level is on average negative and significant, but null at a larger geographical level, such as at the city level. Similarly, the average immigration-crime association is null in cross-sectional studies, while the association is significant and negative in longitudinal studies.

II. Early Thinking of Immigration and Neighborhood Crime

The "Chicago School" scholarships provide a foundation to understand the immigration-crime link at the neighborhood level. This body of work underscores how demographic shifts and urbanization give rise to diverse social phenomena, ranging from the use of leisure time activities to the occurrence of crime. In this line of thinking, Shaw and McKay developed social disorganization theory, which contends that structural conditions such as poverty, residential mobility, and racial-ethnic composition of the community propel a community to be "socially disorganized" and criminogenic.

In *Juvenile Delinquency and Urban Areas* (1942), Shaw and McKay argue that socially disorganized communities lack control, from neighborhood institutions, families, and neighbors, over children's behavior, which leads to higher levels of delinquency in a neighborhood. Hence, as a neighborhood experiences disadvantageous structural conditions, it becomes less able to control residents' behavior and reinforces conventional values and activities that lead to a higher prevalence of crime. Although Shaw and McKay never articulate a clear causal model for their Social Disorganization theory (Kornhauser, 1978), their work represents one of the first attempts to model why some communities harbor more crime than others.

Despite the limitations and modern development of social disorganization theory, Shaw and McKay (1942) propose one of the first conceptual models to consider the role of immigration on neighborhood crime. Shaw and McKay (1942) argue that social disorganization and its attendant influences on neighborhood crime are often the products of ethnic heterogeneity in the communities, indicated by a mixture of populations with diverse backgrounds, cultures, and languages in one place. This ethnic heterogeneity limits the breadth of the social network within a community, which is crucial for the development of social control (Bursik & Grasmick, 1993). At the time of their study, ethnic heterogeneity was generally the byproduct of immigration. Cultural frictions and language barriers were seen as ineffective communication within the community, preempting the development of harmonious social relations and consensus in social norms that control deviant behavior and protect residents from criminal influences.

Meanwhile, an ethnically heterogenous community may experience cultural conflicts, especially between parents and their children, that further delinquency and crime in the area. As immigrants settle down and start families, their children may adopt the behaviors and values of the host neighborhood. These values not only may differ from those of their immigrant parents, which introduce conflicts among family, but also contradict conventional pro-social values that incentivize criminal behavior. As the consequences of cultural conflicts, community social control weakens and children may choose to participate in the delinquent group and involve in criminal activities (Shaw & McKay, 1942).

While Shaw and McKay consider the influence of immigration on crime as the function of ethnic heterogeneity in a community, immigrant neighborhoods today are less ethnically heterogeneous and more homogeneous. In the context of this dissertation, I define an immigrant neighborhood as a community that has a relatively higher prevalence of immigrants, rather than a dichotomous immigrant/non-immigrant neighborhood. In their original study, immigrants in the early 1900s in Chicago were people, or the descendants of the people, from European countries like Germany, Ireland, Italy, Poland, etc. Although they were racially Caucasian, immigrants at the time were very ethnically diverse. Due to such ethnic heterogeneity, communities experienced conditions that made them socially disorganized, disable informal social control, and led to crime and delinquency. Informal social control here is defined as a neighborhood's ability to supervise its residents' behavior and foster conventional socialization, such as two-parent households and viable schools (Vélez, 2014).

However, due to shifting migration trends and settlement patterns of immigration in U.S. communities in recent decades, the proposed mechanism of how immigrants influence crime in the social disorganization theory has become less compatible. When one considers immigrant communities today, certain "ethnic enclaves" such as places like Chinatown, Koreatown, Little Italy, or Little Havana may come to mind (Espinoza-Kulick et al., 2021). The concept of ethnic enclaves, which usually refer to the concentration of an ethnic group within a geographical area, was first introduced in Wilson and Portes's work (1980) studying Cuban immigrant businesses in Florida. Later, Portes specified enclaves

as “immigrant groups which concentrate in a distinct spatial location and organize a variety of enterprises serving their ethnic market and/or the general population” (A. Portes, 1981, pp. 290–291). Thus, ethnic enclaves are often associated with the so-called ethnic economy. As their names imply, these communities mostly consist of members of the same ethnic-racial group, culture, or national origin – that is they are racially, ethnically homogenous.

This geographic clustering of immigrants along racial and ethnic lines is widely documented in the scholarship. For example, In *One Out of Three*, a book that discusses immigrants in New York City over the last two decades, Foner (2013) describes how “many neighborhoods of the city have taken on a distinct ethnic character” (p. 16). In New York City, there are concentrations of Russian Jews in Brooklyn’s Brighton Beach; Central Asian Jews in Queens’ Forest Hills and Rego Park; Chinese in Flushing and Sunset Park; Dominicans in Manhattan’s Washington Heights, Morris Heights, and Tremont; and West Indian in Brooklyn’s Crown Heights and Flatbush. These neighborhoods defined on racial/ethnic lines demonstrate the ethnic homogeneity within immigrant communities today.

Today the concentration of co-ethnics into similar communities is a different pattern from the 1930s, and the co-ethnic clustering has helped build strong social ties and networks that allow for effective communication, social support, resource exchange, and consensus building on community matters. These are the necessary characteristics of social organizations that build immigrant social capital. Despite the variation in the definition and usage of the term social capital, Portes (1998)

recognized that “social capital stands for the ability of actors to gain benefits by virtue of membership in social networks or other social structures” (p. 6). The key is the connectedness of social networks that promotes positive norms and behavior – thus social capital is resources that are realized through relationships (Coleman, 1990). More importantly, “social capital is lodged not in individuals but the structure of social organization” (Sampson et al., 1999, p.634), meaning social capital is embedded in social organization/institutions such as family, friends, churches, etc. Thus, the strong social networks and relationships within modern immigrant communities provide the bedrock for these places to build social organization and garner resources that constitute immigrant social capital (Coleman, 1990; Putnam, 1993; Sampson et al., 1999).

Immigrant social capital, or the beneficial resources from social organization, originates from social networks that share (1) obligations and expectations, (2) information channels, and (3) social norms (Coleman, 1990; Bankston, 2014; Kao, 2004), and I argue these elements enable immigrant revitalization. First, relationships within social networks provide a set of reciprocal obligations and expectations within groups (Coleman, 1990; Kao, 2004). For example, if one neighbor watches another neighbor’s house while they are on vacation, the former might expect the same of the latter in the future – meaning both neighbors enjoy immediate access to resources (of surveillance). These expectations of reciprocal altruism enable a community to build informal social control and prevent crime.

Second, social relations constitute social capital by providing information that facilitates actions (Coleman, 1990; Kao, 2004). For instance, new immigrants

may hear of job opportunities from previous generations of immigrants, and children can learn more about educational resources and career options from their well-educated parents. Effective communication among residents is another way to develop neighborhood social control and reduce crime.

Lastly, established social norms in the social network can reward positive behavior and sanction negative behavior (Coleman, 1990; Kao, 2004). For example, if all community members partake in a neighborhood watch, there is a collective expectation to report suspicious behavior in the area. However, if for some reason one member is found to be negligent and intentionally did not report an instance of suspicious activity, this can fracture the mutual social trust and lead to a spiral of disorder within the community. Vigilant neighbors can decide to exclude the negligent neighbor from enjoying the benefits of the neighborhood watch program while preserving the benefit for those who contribute to the watch. Combined with setting obligations and expectations, establishing and reinforcing pro-social social norms are another powerful way for a social network to develop community social control that buffers neighborhood crime.

These benefits of immigrant communities, also known as ethnic enclaves, have been widely documented in studies in Mexican, Korean, and Vietnamese communities (See Bankston (2014) for case studies). Moreover, these forms of immigrant social capital are also important characteristics for a neighborhood to exert control over residents' behavior and protect them from crime. Hence, the *homogeneity* in immigrant neighborhoods today is more likely to make these

places socially organized, and likely less criminogenic, than the heterogeneous immigrant communities back in the early 1900s.

III. The Current Thinking: Immigrant Revitalization Perspective

Although the traditional theoretical arguments suggest immigration increases crime because ethnic heterogeneity disrupts the social organization of the community and creates competition in the local labor market (Beck, 1996; Butcher & Piehl, 1998; Reid et al., 2005; Shaw & McKay, 1942; Waldinger, 1997), most current research supports the "immigrant revitalization perspective" whereby immigration buffers or even reduces neighborhood crime by revitalizing the local communities. As Lee and Martinez (2002) articulated, "Immigration revitalizes poor areas and strengthens social control (thereby decreasing crime) due to strong familial and neighborhood institutions and enhanced job opportunities associated with enclave economies" (p. 366).

According to the immigrant revitalization perspective, there are three main ways in which immigration revitalizes neighborhoods by bringing in social organization that produce immigrant social capital: (1) strengthening the familial institution and thereby private social controls – a form of informal social control that operates through close friends and families; (2) invigorating the local economies and providing new job opportunities; and (3) developing community institutions that facilitate social control (Hunter, 1985; Kubrin & Ishizawa, 2012; Lee et al., 2001; Lee & Martinez, 2002; Reid et al., 2005; Vélez, 2009).

First, immigrants usually have strong social ties with their family members, friends, co-ethnic fellow residents, and other non-kin community persons like

clergy and school officials (Vélez, 2009). In an immigrant-concentrated neighborhood, these positive familial and fictive kinship and social supports help the community to establish community social capital, producing private and informal social control that eventually mitigates crime and delinquency (Kubrin & Desmond, 2015).

Second, the influx of newly arrived immigrants helps reinvigorate the local economies by bringing in businesses and job opportunities for both immigrants and the native-born population (Reid et al., 2005). Immigrants with fewer skills and less education could face labor market discrimination from native-owned companies (Zhou, 1995). In this situation, the presence of ethnic businesses, as a form of immigrant social capital, helps immigrants access employment in businesses owned by co-ethnics without discrimination (Bankston, 2014; Zhou, 1995). With these job opportunities, residents of immigrant neighborhoods should be more attached to the labor market as they spend longer time at work and build connections with coworkers. Attachment to the labor market is beneficial in preventing crime in a community, because residents are more likely to commit to conventional daily routines and build attachments to jobs or coworkers that develop a stake in conformity. These attachments keep themselves and their co-residents away from criminal activities. In this case, immigrant communities with strong economics are more likely to provide social capital that makes the community less conductive to crime, while also exerting public social control – another type of social control expressed via social ties between neighborhood residents and government and nongovernment institutions (e.g., workplaces, local

businesses, community center, and police/fire station) that helps to control crime (Bursik & Grasmick, 1993; Hunter, 1985).

Moreover, through expanding these government-supported resources, immigrant communities can better secure public goods and services outside of the neighborhood and mobilize such resources to control crime. These benefits are not only enjoyed by immigrants but by all community members. Areas with more recent immigrants can expand resources devoted to community services and safety, leading to an increase in well-paid community service jobs (e.g., jobs in police, fire, health, and legal departments) (Reid et al., 2005). Since these types of jobs usually go to native-born workers, increased economic opportunities in these areas are also expected to have lower levels of property crime for all residents in the community (Rosenfeld & Tienda, 1999). Thus, immigration produces social capital that strengthens local public social controls by bringing in business, job opportunities, and public resources that benefit both immigrants and non-immigrant residents of the community.

Lastly, immigration bolsters and empowers local social institutions like churches and schools to act as brokers to improve neighborhood well-being (Vélez, 2009). These immigrant-serving organizations provide resources that help immigrants settle in their new communities and promote cultural diversity in the neighborhood (Kim et al., 2022). For instance, Ley (2008) finds that the influx of immigrants in Canada helped to strengthen neighborhood churches by promoting social networks and delivering personal and social services to residents. Moreover, immigrant-serving organizations help to strengthen social ties and

facilitate informal social control because they help immigrants integrate into the community and participate in local activities (Kim et al., 2022). Community institutions like churches, organize activities for social networking provide programs for youth, bridge communities to mainstream individuals and institutions, and bring in external resources for the neighborhoods (Bursik & Grasmick, 1993; Vélez, 2006). Hence, by expanding and strengthening community organizations, immigration helps neighborhoods develop informal social control that translates into lower levels of crime.

In this study, I argue immigrant social capital is the driving force of immigration revitalization in the neighborhoods. The close-knit social ties within the immigrant community reinforce the reciprocal *obligations and expectations* to take care of families and extended kin and deprecate divorce and family disruption (Morenoff & Astor, 2006; P. A. Portes & Rumbaut, 2001). This phenomenon also resembles the concept of familism, which will be further discussed in the next section. Due to shared experience of migration and a higher level of network closure, immigrant communities can further reinforce these *social norms* and control residents' behavior, especially through immigrant parents' control over the second generations which ultimately prevents youths' involvement in criminal activities (Kao, 2004; Portes & Rumbaut, 2001). Lastly, immigrant communities enable *information channeling* about employment, housing, and access to goods and services while invigorating the local economy and developing local institutions (Bankston, 2014; Fong & Berry, 2017; Vélez, 2009).

More importantly, these characteristics of immigrant social capital encompass the ingredients for a community to develop and exert community social controls that keep crime at bay. Linking back to the systemic model of social organization theory, the closeness and extensiveness of social networks are the key factors that control neighborhood crime (Bursik & Grasmick, 1993; Hunter, 1985). Empirically, Sampson and Grove (1989) find that a community with strong local friendship networks has less street robbery and total victimization, while high organizational participation is associated with less robbery, violence, and total victimization. Similarly, in the literature on collective efficacy, mutual trust and willingness to intervene among residents are the keys for a neighborhood to maintain social control in the community that is linked to lower levels of crime (Sampson et al., 1997). The idea of "social cohesion among neighbors combined with their willingness to intervene on behalf of common good" (Sampson et al., 1997, p. 918) mirrors sources of social capital that, in many ways, one can also argue that social capital *is* collective efficacy (Sampson et al., 1999). Hence, I argue immigration, by revitalizing neighborhoods, builds immigrant social capital, facilitates social control in the community, and makes it a safer place.

In sum, immigrant communities enjoy high levels of social capital, mainly demonstrated by rich interpersonal networks and strong interpersonal ties, including family connections – both of which contribute to the community-oriented nature of immigrant communities (Portes & Rumbaut, 2006; Portes & Stepick, 1993; Portes & Rumbaut, 2001; Wilson, 1996). Moreover, dense communal social networks can assist new immigrants in assimilating into the

local community by bridging language barriers, navigating immigration processes, and accessing vital safety net resources. This social support provides newcomers with a sense of belonging and diminishes structural disadvantages conducive to crime (Feldmeyer et al., 2019; Kubrin & Desmond, 2015). The strong social networks among immigrant families and co-ethnics enhance social controls that help to control crime and delinquency in the neighborhood. For instance, Vélez (2009) finds that in extremely disadvantaged neighborhoods, the increasing number of recent immigrants is associated with less homicide in the neighborhood. Thus, strong immigrant social capital might be the engine behind how immigration revitalizes neighborhoods and reduces crime because it diminishes crime-generating structural disadvantages and promotes social control in immigrant neighborhoods.

In the next two sections, I will discuss the role of family structure and local economy as the key social institutions that produce immigrant social capital, the first and second pathways in the immigrant revitalization process discussed above, and how they may influence neighborhood crime.

Immigration, Family Structures, and Neighborhood Crime

I. Family as a Dimension of Immigrant Social Capital

As immigrants move into our communities, families of immigrants are discernibly different from those of native-born American families on average. First, immigrants are more likely to form intact (two-parent) families compared to the native-born population. Between 2008 and 2012, while immigrants comprised

roughly one-eighth of the U.S. population, one-sixth of marriages involved an immigrant. More than one-half of these marriages included a native-born partner (Budiman, 2020; Lichter et al., 2015). While the probability of endogamous marriages (among natives or immigrants) remained high, the trend of intermarriage, defined as marriage between partners from different ethnic or racial groups or national origins, has significantly increased over time (Lichter et al., 2015; National Academies of Sciences & Population, 2016). Foreign-born adults in the U.S. are also more likely to get married than the native- born. According to the 2016 American Community Survey (ASC) 1-year estimates and the 2014 Survey of Income and Program Participation, about 76% of foreign-born adults have ever married, compared to 67% of U.S.-born adults (Mayol-García et al., 2021).

Second, besides their higher marriage rate, immigrant families are more stable, meaning they are less likely to divorce or stay in their first marriage. For adults who ever married, immigrants are less likely to have ever divorced (20%) and less likely to be re-married (14%) compared to the native-born population (36% and 26%, respectively) (Mayol-García et al., 2021). Foreign-born persons are also more likely to stay in their first marriage than their U.S.-born counterparts. Using the 2019 ASC microdata from IPUMS, approximately 72% of immigrants with children are in their first marriage while the share of U.S.-born is only 60% (Wang, 2021). Although more likely to be in a disadvantaged and impoverished circumstance, immigrant parents tend to stay together. More than half of the immigrant children live in families that are poor or near-poor, while

less than 40% of children of U.S.-born parents live in poor or near-poor families (Zill, 2016).

Another dimension that shows the stability of immigrant families in the U.S. is children living in immigrant families. Here, an immigrant family is defined by having at least one foreign-born parent. A recent report from the Urban Institute shows that one out of every four children in the U.S. has at least one immigrant parent (Lou et al., 2019). Moreover, children of immigrants are also more likely to live in traditional two-parent married households compared to native-born ones (National Academies of Sciences & Population, 2016; Zill, 2016). For example, according to the 2012 American Community Survey (ACS), 57% of Mexican and 77% of Indian families are headed by a married couple (Menjívar et al., 2016). These statistics demonstrate that immigrant families are a prevalent part of the social fabric and contribute to family stability in the U.S.

Lastly, immigrant families are not only more likely to form stable, intact two-parent households but also more likely to be multigenerational (Fry & Passel, 2014; National Academies of Sciences & Population, 2016). A family is multigenerational when three or more generations are living under one roof (Keene & Batson, 2010). For example, a household with a married couple, children, and the children's grandparents is considered a multigenerational family. A recent Pew report finds that foreign-born persons are more likely to live in multigenerational households than U.S.-born persons (26% versus 17%, respectively) (Cohn et al., 2022). While many factors have contributed to the rise of multigenerational households since the 1970s, the changing makeup of the U.S.

population, especially the population growth of immigrants, Asian, Black, and Hispanic Americans, is one of the major contributors to this trend.

As immigration shapes families in our communities, these stable and multigenerational families could reinforce familism – which shares characteristics of social capital – in immigrant communities that help to build social control, specifically informal social control. Familism is defined as "strong in-group feelings, emphasis on family goals, common property, mutual support, and desire to pursue the perpetuation of the family" (Bardis, 1959, p. 340). Meanwhile, again, social capital is characterized by a closed network that has reciprocal values and norms that result in behavior outcomes that are beneficial to all parties of the network (Coleman, 1990). As immigrant communities have more stable and/or multigenerational families, the strong social ties within the community encourage social norms of achieving family goals, exchange of emotional and financial support, and mutual obligations and expectations on accomplishing those goals and providing resources. In this case, the presence of stable families and multigenerational families is a manifestation of social capital. Because immigrant groups are more likely to form stable and supportive family structures, I hypothesize immigrant neighborhoods to be more likely to develop familism, which shares the features of immigrant social capital that helps to revitalize communities.

The stability and multigenerational structures of family illustrate familism in immigrant families. Immigrants, especially immigrant families from Mexico and Southeast Asia, are more family-oriented and are more likely to reinforce the

traditional intact family structure and place greater value on marriage (Brooks, 2006). For instance, in 2019, among immigrants with children under 18, 94.3% of Indians, 85.1% of Koreans, 76.9% of Vietnamese, 67.7% of Mexicans, and 62% of Colombians were still in their first marriage. Especially in the case of newly arrived immigrants, living in multigenerational households provides the necessary social capital to help them start their lives in a new land and navigate hardships such as seeking employment and housing.

Familism has been widely acknowledged in East Asian culture, where the influence of Confucianism promotes strong familial responsibility for the elder parents or grandparents (Kamo, 2000). The benefits of stable family structures are also illustrated in Latino culture in the concept of *familismo* (Calzada et al., 2013; Sabogal et al., 1987). In a qualitative study of low-income neighborhoods in New York City, Calzada and colleagues (2013) found that *familismo* is specifically revealed through financial support, shared living, and shared childrearing. For example, the authors commonly found that financial exchanges were formalized through a practice called *tanda* where family members pooled savings, with the proceeds being given to one of the contributors to alleviate financial hardships such as paying monthly bills and caregiving. Families would take turns using this process, developing financial support networks in the process. Although maintaining familism necessitates high emotional and financial costs – especially for low-income families, family members still engage in family-oriented behaviors for the support that *familismo* offers.

Knowing immigrant neighborhoods are more likely to have stable and multigenerational families, I argue higher prevalence of immigrants in a community fosters familism as a form of immigrant social capital, which could be a stepping-stone by which immigration produces greater community social controls that impede crime in the communities. To achieve that, members of immigrant families "engage in social exchanges that give rise to mutual dependence and expectations" and "duties encompassing sexual, child-rearing, and productive activities" (Sanders & Nee, 1996, p. 233). Especially for multigenerational immigrant families, grandparents often serve as an extra source of social support. Prior research illustrates the significant contribution of grandparents to immigrant families, including but not limited to childcare, household chores, emotional support, and transmitting cultural traditions from the home country (Casper et al., 2016; Menjívar et al., 2016). For families in a more socially disadvantaged environment with working parents, grandparents are the most "affordable" and reliable source of care and supervision for the family's children (Silverstein & Lee, 2016). While immigrant families are one of the main sources of immigrant social capital that provide resources and exert informal social control (Sanders & Nee, 1996), little attention has been paid to how family structures play a role in mediating the relationship between immigration and neighborhood crime.

II. Family Structures and Neighborhood Crime

The above section shows how immigration brings about stable and multigenerational families in the neighborhood and bolsters social control. This

begets the following question: why do these family structures matter in predicting neighborhood crime? Existing literature has already shown the connections between the two both theoretically and empirically.

First, social disorganization theory suggests that certain structural conditions of the neighborhoods, including poverty, ethnic heterogeneity, and residential instability, explain higher rates of delinquency in inner-city neighborhoods (Shaw & McKay, 1942). Neighborhoods with these structural disadvantages are more likely to be socially disorganized, which means they are incapable of developing social controls that curb crimes (Bursik & Grasmick, 1993). More relevantly, the theory suggests that the ability of a community to supervise and control youth activities (specifically gang-related activities at the time) explains how social disorganization is related to crime (Sampson & Groves, 1989; Shaw & McKay, 1942). Specifically, family structures matter because two-parent households and multigenerational households provide increased supervision on not only their children but also household property (Sampson & Groves, 1989). Since parents or grandparents are the key players in supervising teenagers' behavior, neighborhoods with more stable families and multigenerational families are more capable of collectively overseeing otherwise unsupervised teenage activities, one form of strong social control.

In an empirical testing of social disorganization theory, Sampson and Groves (1989) specify and test the intervening dimensions of social disorganization by examining how low economic status, ethnic heterogeneity, residential mobility, urbanization, and family disruption influence crime and delinquency through local

friendship network, unsupervised teenage groups, and low organizational participation. Most relevant for this dissertation, they found that the level of family disruption directly increases neighborhood violent victimization. More importantly, family disruption is also indirectly associated with a higher level of violent and property victimization through increasing unsupervised activities among teenagers and diminishing local friendship networks. These findings imply unstable family structures disable supervision over youth's behavior and their social networks, thereby increasing the risk of criminal victimization because it. Hence, family stability is crucial in in developing community social controls that regulate crime and delinquency.

It is important to note the influence of family stability is not at an individual level (i.e., family structures do not determine whether an individual is more or less likely to commit a crime). Instead, the effect is structural; disregarding one's family situation, youth residing in areas with more stable families are more likely to be subjected to local supervision in their leisure activities. Especially for the immigrant community, this phenomenon is documented in qualitative studies. For example, when living in a Mexican-immigrant neighborhood, Dohan (2003) observed that residents often gathered to socialize and supervise kids' activities in public areas. Scholars have also argued that a dearth of stable families is a proxy for overall disorganization and a lack of social control for adults as well (Blau & Blau, 1982; Sampson, 1986). In connection with familism in immigrant families, a study of Mexican and Mexican American adolescents found that familism and family cohesion significantly reduce aggressive behavior, conduct problems, and

rule-breaking (Marsiglia et al., 2009). For these reasons, a stable family is as important for juveniles as it is for adults in the neighborhoods since it could diminish community social control. In a nutshell, neighborhoods with more stable families are more likely to be socially organized rather than disorganized because they possess the ingredients to develop strong private social ties and community informal social controls, which further reduces neighborhood crime (Bursik & Grasmick, 1993; Hunter, 1985).

Another theory that discusses how family structures could affect crime in a community is the routine activity theory. Routine activities mean "generalized patterns of social activities in a society (i.e., spatial and temporal patterns in family, work, and leisure activities)" (Wikström, 2009). The key idea is that while structural conditions in a society influence one's routine activities, collective routine activity patterns produce situations that are conducive to crime. Specifically, crime incidents are most likely to occur in places where there is a convergence of a motivated offender, a vulnerable target, and a lack of capable guardians (control/supervision) (Felson & Cohen, 1980; Wikström, 2009). This is important in the context of family structures, where presence of family members could proxy for capable guardianship. Thus, in a community that has more stable families, there may be more capable guardians to reduce criminal opportunities and curb crime and delinquency.

Empirically, Sampson (1986) considers both social disorganization and the routine activities theory and examines the effect of family structure on the risk of victimization. Using percent divorced, percent female-headed households, and

primary individual households as proxies for lack of stable families and guardianship, he finds that places with low levels of stable families and high levels of primary individual households have significantly higher risks of theft and violent crime.

Multigenerational families could provide an extra layer of neighborhood supervision and support when the householders, usually the parents of the family, are occupied. However, few studies investigate the relationship between multigenerational families and neighborhood crime while the benefits of stable family structures are widely acknowledged. Most of the literature regarding multigenerational families and crime is at the individual level and only considers multigenerational families with family violence, mental and behavioral health of the children, family conflicts, and self-reported violence and aggression. Although most of these studies find an adverse influence of multigenerational families on children's well-being, multigenerational families could be beneficial to neighborhood well-being by increasing the level of familiarity within the neighborhoods and providing resources (Pattillo, 1998). As illustrated earlier, immigrant families are more likely to be multigenerational and receive the benefits of enhanced family bonds and family support (emotionally and financially) – stronger immigrant social capital. Thus, following the literature on stable family structures, I argue multigenerational families are another important element undergirding immigrant social capital that helps to improve social controls and guardianship in the community and prevent neighborhood crime.

Immigration, Local Economy, and Neighborhood Crime

According to the immigrant revitalization perspective, besides strengthening familial institutions, immigration revitalizes communities by bringing new businesses and job opportunities (Kubrin & Ishizawa, 2012; Lee et al., 2001; Lee & Martinez, 2002; Vélez, 2009). Specifically, strong social networks within immigrant communities enable information channels, especially about jobs, that help these communities to build social capital and social control. This section discusses how immigration is the backbone of U.S. economy. It especially underscores the role of immigration in revitalizing the local economies in immigrant neighborhoods, and how these local economies can produce a protective or a detrimental effect on neighborhood crime.

I. Local Economy as a Social Organization of Immigrant Social Capital

Immigrants have played a central role in revitalizing neighborhoods, primarily by creating local businesses. Zhou (2013) provides a good example of such a revitalization process in Sunset Park, a neighborhood in Brooklyn, NY, which experienced an exodus of European middle-class families in the 1950s, leaving absentee-owned houses and vacant storefronts. From 1980 to 2000, the share of the non-Hispanic white population decreased from 51% to 22%. Meanwhile, working-class Chinese who newly arrived in New York seek new residence in the area, increasing the ethnic Chinese share of the population in Sunset Park from 4% to approximately 25%. This new injection of Chinese immigrants led to the creation of many new retail stores, service businesses, and garment factories where they and their fellow immigrants could work and shop. Today, Sunset Park

is a thriving community that provides accommodations and needs for immigrants, as well as culinary diversity in the city. A 2016 report from the Office of the New York State Comptroller describes Sunset Park as a safe immigrant community with strong business growth and record-high job growth (Office of the New York State Comptroller, 2016).

As exemplified by Sunset Park, contemporary immigration revitalizes the local economy by incubating new businesses in their communities and providing employment opportunities for their residents, as the immigrant revitalization perspective suggested (Kubrin & Ishizawa, 2012; Ousey & Kubrin, 2009). When arriving in a new environment, immigrants tend to seek familiarity in food, services, and products from their home cultures. In accommodating these needs, immigrant businesses often find their places within immigrant communities (Fong & Berry, 2017; Light & Gold, 2000), and this concentration of local businesses constitutes a so-called "ethnic enclave economy." The ethnic enclave economy is a fundamental part of immigrant social capital because it is characterized by "the presence of immigrants with sufficient social capital to create new opportunities for economic growth and extensive ethnic division of labor" (Vélez, 2009, p. 327).[1]

[1] The advantageous influence of immigrant business on neighborhood well-being is widely recorded, but little work discussed the potential disadvantageous influence on the community. However, it is important to acknowledge that literature at the individual level shows immigrants working in enclave economy/immigrant business often face hardships such as limited job upward mobility, exploitation of labor, especially from family members, and increased competition and conflicts across different immigrant groups (Bankston, 2014).

Local businesses and entrepreneurship are visibly embedded into the tapestry of ethnic enclaves. As Fong and Berry (Fong & Berry, 2017) state, "from Frankfurt to Rome in Europe, from Taipei to Singapore in Asia, and from Vancouver to New York in North America, immigrant businesses are a visible presence" (p. 64). According to the Office of Advocacy of the U.S. Small Business Administration (SBA), the shares of both immigrant employers and foreign-born workers have increased over the past ten years. As of 2020, 19% of the business owners are immigrants, while about 9% of the workers are foreign-born (Gotliboym, 2023). Similarly, the 2016 American Community Survey shows that about 20% of foreign-born workers were self-employed compared to 9% of native-born workers (Christnacht et al., 2018). In a recent study on immigration and entrepreneurship, scholars show that immigrants in the U.S. are more likely to start businesses compared to the U.S.-born population (Borjas, 1986; Christnacht et al., 2018; Dávila & Mora, 2013; Fairlie & Meyer, 2003; Azoulay et al., 2022). Moreover, their analyses reveal that immigrants are more likely to be "job creators" than "job takers," which counters literature that argues that immigration increases labor market competition and lowers wages for native-born workers (Christnacht et al., 2018).

Research suggests the immigrant predisposition to entrepreneurship is largely the product of labor market discrimination and language barriers (Lee et al., 2001; Light & Gold, 2000; Orozco, 2020; Waldinger, 1993). Public concerns about immigrants taking jobs away from the native-born population (along with their lower level of education, skills, and familiarity with English) have often pushed

immigrants away from seeking jobs in mainstream society (Bankston, 2014; Lee et al., 2001; Shihadeh & Barranco, 2010a, 2010b). This is especially true for immigrant groups such as Latinos who have historically faced strong labor market discrimination (Catanzarite & Trimble, 2008). As shown in the 2021 Annual Business Survey, Hispanic employers made up about 6.5% of all business owners, which is ranked second among all minority groups behind Asians (Lee, 2023). Hence, one can argue that the high prevalence of immigrant entrepreneurship signal labor market discrimination.

Apart from labor market discrimination, immigrants could be motivated to seek and retain employment in the U.S. due to the lackluster economic conditions and scarce job opportunities in their home countries – what some called the "host-country effect" (Durand & Massey, 2004; A. Portes & Rumbaut, 2006; Stansfield, 2014). Although many immigrants tend to work in low-paid service sector jobs due to a lack of education and skills (Abrego & Gleeson, 2014), a large share of them also choose to become self-employed for greater economic advancement (Sanders & Nee, 1996). The economic improvement through entrepreneurship can be shown by their higher earnings relative to their native counterparts.[2] For instance, during the 1980s, self-employed Chinese and Cuban immigrants had

[2] It is important to note that not all immigrants can easily become self-employed. Existing literature suggests that there is a selectivity among different immigrant groups in the predisposition to become a business owner. Ethnic minorities or immigrants who have greater wealth (Geoscape, 2106), advanced education (Bates et al., 2018), and come from a better socioeconomic status (Valdez, 2011; Vallejo & Canizales, 2016) are more likely to start their own businesses.

average annual incomes of $43,151 and $36,558, compared to $29,721 and $26,510 for native salaried workers, respectively (Sanders & Nee, 1996).

In sum, ethnic entrepreneurship creates jobs for fellow co-ethnics and provides them the opportunities to succeed in economic upward mobility. Empirical evidence demonstrates that immigrant business owners are open to hiring co-ethnic or other minority workers, especially those who are less educated and possess few skills (Bankston, 2014; Fong & Berry, 2017; Sanders & Nee, 1996; Zhou, 2013). By bringing in new businesses and job opportunities, immigration helps to build an ethnic enclave economy and produce immigrant social capital.

II. Local Economy and Neighborhood Crime

While a vibrant local economy in immigrant communities reflects strong immigrant social capital that enables information channeling, it is less known how this influence reduces neighborhood crime. There are a few theoretical frameworks that suggest ethnic enclave economies revitalize local communities and reduce neighborhood crime by (1) bringing in new businesses and job opportunities, (2) providing a place for social interaction, and (3) keeping the area under a higher level of guardianship.

First, the literature on the economy and crime emphasize the importance of labor market involvement and crime, whereby employment provides stability and regulates daily behavior that encourages people to commit consistent schedules and conventional activities (Blau & Blau, 1982; Cloward & Ohlin, 1960; Cohen & Felson, 1979; Crutchfield, 1989; Crutchfield & Pitchford, 1997; Hirschi, 1969;

Laub & Sampson, 1993; Merton, 1938; Toby, 1957; W. J. Wilson, 1996). As immigration increases, immigrants brings businesses and jobs that could boost the benefits of labor market involvements. According to the 2012 Survey of Small Business Owners (SBO), minority-owned businesses contributed 7.2 million jobs to the U.S. economy (McManus, 2016). Another report shows that about 14% of people who were employed by small businesses worked in immigrant-owned businesses (Kallick, 2012). The businesses immigration bring about are important as minority-owned businesses might act as community role models and foster a culture of hard work and engagement in the formal economy (Stansfield, 2014). As a result, these minority-owned businesses in the neighborhood become sources of social capital that help residents stay employed and adhere to conventional daily activities, increasing informal social control in the process. These beneficial consequences of the immigrant revitalization process could protect the community from crime.

Second, local businesses, especially small businesses, can promote ties and community social control in the area by increasing social interaction among locals. Locally owned businesses are "owned and run by an entrepreneur based in the local area, primarily targeting the local population to provide goods and services" (Kim & Hipp, 2022, p. 2). This aligns with the characteristics of ethnic enclave economies that serve the needs of local immigrants. These small businesses embody the concept of "third place" where people engage in social interaction outside of home and work, furthering social cohesion among residents (Williams & Hipp, 2019). Some examples of third places are local restaurants,

coffee shops, and ice cream parlors (Kim & Hipp, 2022). In these third places, people run into each other when doing errands in the same community and engage in small talk and information exchange. Customers, mostly locals, may become more recognizable and less anonymous when visiting local businesses over time. As a result, these businesses are more likely to develop into hubs of social activities and interactions among residents, thus increasing informal social control in the neighborhoods.

Moreover, these repeated social encounters among known neighbors could promote social trust and social cohesion in the community (Kim & Hipp, 2022; Lawler, 2001; Lawler & Yoon, 1998). It is also important to note that local businesses are embedded in the local social networks that actively engage in market information exchange and mutual learning that depend on mutual trust. Besides creating opportunities for residents' social interactions, the strong cohesion and mutual trust among local businesses can further strengthen the social ties between business owners and their employees, setting the conditions for robust neighborhood social control (Johannisson et al., 2002; Johannisson & Nilsson, 1989; Kim & Hipp, 2022).

Prior research provides empirical evidence on how a thriving local economy consolidates immigrant social capital in immigrant neighborhoods, which is beneficial to crime control. Kim and Hipp's (2022) study shows that the concentration of local businesses has a significant crime-buffering effect for the areas they were located in. Although the number of businesses is positively associated with both violent and property crime, areas that have more local

businesses have significantly smaller crime-enhancing effects compared to places that have more non-local businesses. These crime reduction benefits can be specifically true for immigrant-owned businesses because they are generally small and hire family/relative members and co-ethnics (Fong & Berry, 2017; Park, 1997; A. Portes & Bach, 1985; Zhou, 1995). The enriched job opportunities that come along with ethnic entrepreneurship in immigrant neighborhoods help strengthen community social controls and reduce crime (Lee & Martinez, 2002).

Lastly, the number of local businesses can also indicate the liveliness of social and economic activities in an area (Jacobs, 1961). A community with more local businesses means it is a livable area to potential residents and attractive area to visitors. As Kim and Hipp (2022) underscore, these local businesses "represent the amount of local economic consumption by importing and exporting various products, socially interacting with local customers, and providing a social locus for various activities" (p. 5). In this case, locally owned businesses can increase natural surveillance, defined by the ability of inhabitants of an area to observe public areas casually and continually. These "eyes on the street" facilitate and sustain a lively and healthy social ecosystem.

Similarly, constant neighborhood vigilance resembles consistently capable guardianship, in line with the routine activity theory (Cohen & Felson, 1979). A vivid local economy will increase population flow by attracting local customers and visitors, and this increased commercial traffic may not only generate capable guardianships for potentially vulnerable victims but also make the environment less conducive to criminal activities. This also resembles the idea of "institutional

completeness" whereby a community has a high degree of social institutions that include business, religious, recreational, educational, and political domains (Breton, 1964; Kubrin et al., 2019).

In sum, close-knit social relationships, which allow residents to access resources through the network, are the key for a community to develop immigrant social capital. Paired with a strong local economy, residents are more easily able to build social relationships through interactions, which strengthens social capital and social control in the community. Local business and entrepreneurship encourage residents in the neighborhood to work together to diminish structural disadvantages such as unemployment and poverty, stabilize the community, and enable social controls. Lastly, a thriving local economy keeps residents employed and continues to attract immigrants and native customers, keeping "eyes on the streets." Hence, a strong local economy in immigrant communities is another way in which immigration revitalizes neighborhoods by stabilizing the community, enabling community social controls, and increasing the level of surveillance to regulate neighborhood crime.

Yet, businesses may also attract crime (Brantingham & Brantingham, 1984, 1993, 1995; Contreras & Hipp, 2020; Groff, 2011, 2014; Groff & Lockwood, 2014; Kubrin & Hipp, 2016). According to the routine activity theory, business facilities may increase criminal activities by attracting potential offenders, vulnerable victims, and incapable guardians to interact in the same place and time (Cohen & Felson, 1979). Environmental criminologists also suggest that offenders can identify and exploit criminal opportunities in their daily travel from

home to work and regular visits to recreational activities, known as activity nodes, which help to explain differential crime patterns across business establishments (Brantingham & Brantingham, 1995; Kim & Hipp, 2022; Sidebottom & Wortley, 2015). In other words, local businesses are crime generators that attract many visitors, including both people visiting for legitimate purposes as well as potential offenders. This heavy foot traffic increases the probability of convergence of offenders and targets. There are also businesses considered crime attractors, such as bars and marijuana dispensaries, which provide opportunities for criminal behavior (Brantingham & Brantingham, 1995; Kim & Hipp, 2022; Sidebottom & Wortley, 2015). Hence, the number of local businesses in immigrant communities could produce a crime-enhancing effect that is not anticipated by immigrant revitalization processes.

Unfortunately, while ample studies investigate the immigration-crime nexus, there are few explicit examinations of the role of the local economy as the mechanism by which immigration revitalizes neighborhoods and reduces crime. A previous study looking at the prevalence of Hispanic-owned businesses finds that the significant inverse association between immigration and property crime at the city level was explained away after the number of Hispanic-owned firms was included in the author's model (Stansfield, 2014). The author concludes that his findings may indicate immigrant revitalization operating through immigrant-owned businesses. Although the prior effort of considering the mediating effect of Hispanic-owned businesses on the immigration-crime nexus is valuable, it is important to examine the relationship at the *neighborhood level* as the immigrant

revitalization perspective proposes. Only looking immigration-crime nexus at the city level could mask the protective effect of immigration on crime brought about at the neighborhood level. For the relevance of the local economy and the extensiveness of entrepreneurship in immigrant neighborhoods, I argue immigration revitalizes neighborhoods by invigorating the local economy, building social capital, and developing social control and produces protective influence in controlling neighborhood crime.

Present Study

The present study aims to further the understanding of the immigration-crime relationship at the neighborhood level, leveraging various theoretical frameworks, including social disorganization and opportunities theories, and paying particular attention to the immigrant revitalization perspective (again, as indicated in Figure 1). Instead of being racially and ethnically heterogeneous, immigrant communities today are more likely to be racially/ethnically homogenous (Espinoza-Kulick et al., 2021; Foner, 2013; Fong & Berry, 2017). As immigration brings stable and extensive families and local businesses into the community, neighborhoods possess these structural characteristics also indicative of communities have strong immigrant social capital. The mutual obligation and expectation of norms within immigrant groups, especially within families, information channeling of jobs and other resources that overcomes language barriers and limited opportunities in the host country, and the social norms that reinforced through the closed social networks in immigrant communities are not only resources of immigrant social capital but also necessary ingredients for a community to develop social controls that curb crime. Thus, the

immigrant social capital originating from immigrant communities is the way in which immigration revitalizes communities, produces social controls, and reduces crime.

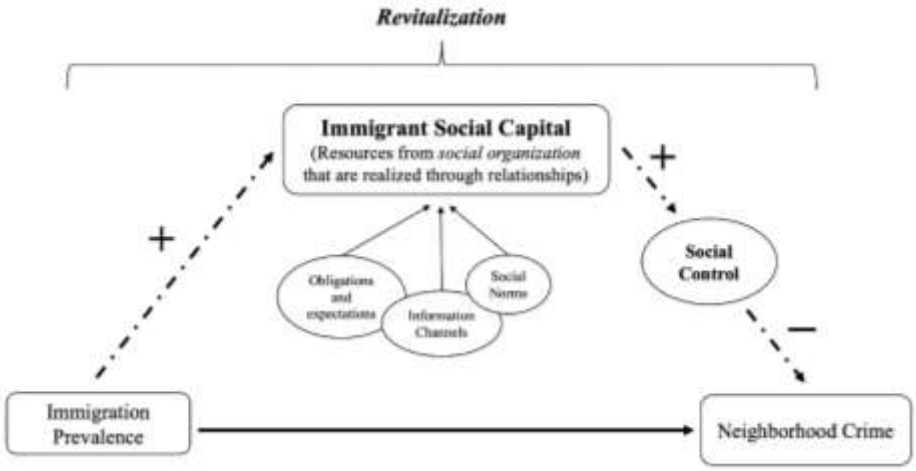

Figure 1: Conceptual Model

Yet, the mechanism by which immigration revitalizes neighborhoods and reduces crime is rarely tested empirically. Although some of the existing studies tried to investigate the mechanisms between immigration and crime, these studies fail to consider (1) the full picture of immigrant revitalization, (2) the stability and extensiveness of immigrant families, and (3) the theory-driven hypotheses at the neighborhood level across various city contexts (Feldmeyer et al., 2019; Kubrin & Desmond, 2015; Ramos et al., 2023). This dissertation seeks to be the first of its kind to address those issues by identifying and assessing the direct and indirect influence of immigration in diminishing crime at the neighborhood level.

To further an understanding of the immigration-crime relationship at the neighborhood level, this dissertation tests the immigrant revitalization perspective and hypothesizes:

a. Based on the immigrant revitalization perspective and existing literature, immigration is inversely related to crime at the neighborhood level.

b. Based on the immigrant revitalization perspective, immigrant prevalence at the neighborhood level produces immigrant social capital by increasing stable and multigenerational families in the neighborhoods and thus preventing crime.

c. Based on the immigrant revitalization perspective, immigrant prevalence at the neighborhood level produces immigrant social capital by bringing in and establishing more businesses in the neighborhoods and thus preventing crime.

Chapter 3: Data and Methods

To answer my research questions, my main analyses use the self-collected National Neighborhood Crime Study 3 Pilot (NNCS3-P) panel dataset to perform mediation analyses of how immigrant social capital facilitates the relationship between immigration and neighborhood crime (Figure 1). The mediation analyses involve (1) fixed effect panel data analyses and (2) temporally ordered mediation analyses. To set up the mediation analyses, I investigate the relationship between immigration and neighborhood crime holding immigrant social capital constant (path *c* in Figure 2) both cross-sectionally and longitudinally to provide a full descriptive picture of the immigration-crime relationship, while path *c'* is the WITHOUT controlling immigrant social capital. I also examine the influence of immigration on immigrant social capital (path *a* in Figure 2) and immigrant social capital on neighborhood crime (path *b* in Figure 2) to establish a mediation model (Baron & Kenny, 1986). In the following sections, I will first briefly discuss the original NNCS data and why it is inadequate for answering the research questions. Then I will delineate the process of data collection for the NNCS3-P and the measures used for the analyses. I end this chapter with detailed analytical strategies and specifying the regression models.

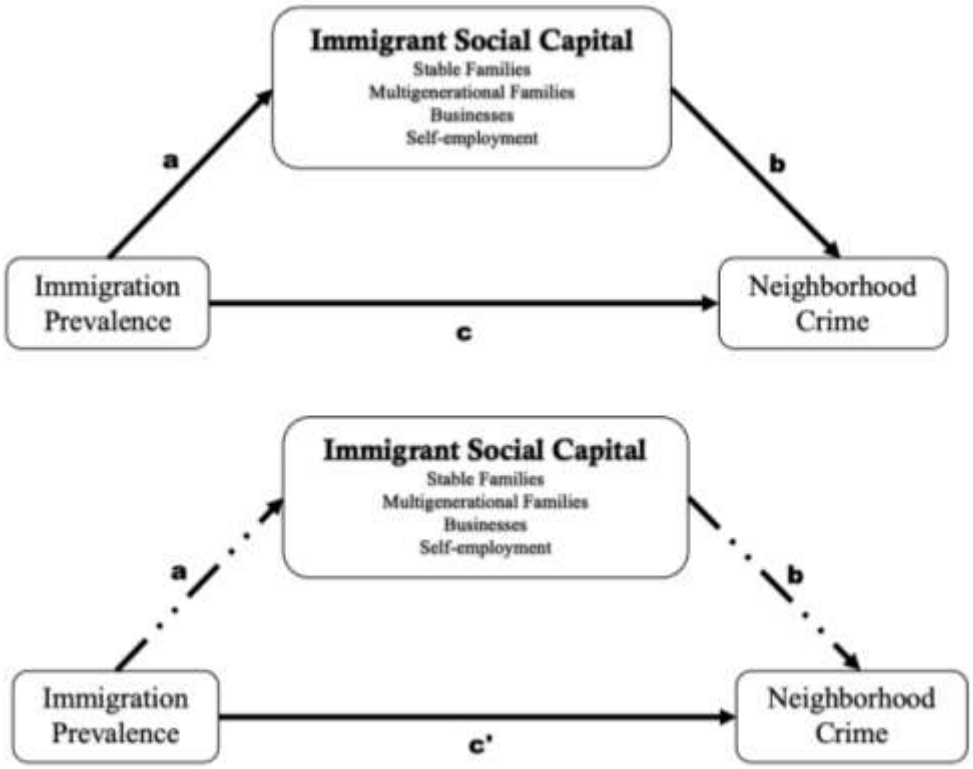

Figure 2. Measurement models for mediation analyses
(Solid lines denote direct pathways; Dashed-dot lines denote indirect pathways through another variable)

The NNCS and Its Limitation for Mediation Analysis

In examining the immigration-crime mechanism, the aspiration is to make a causal inference that immigration affects crime by producing immigrant social capital. Oftentimes, one way to build and test this causal relationship is to conduct a mediation analysis. To establish causation, an analytical tool, like mediation analysis, requires the fulfillment of three criteria: (1) the cause preceded the effect (temporal sequence), (2) the cause was related to the effect (correlation), and (3) the exclusion of all plausible alternative explanations for the effect other than the cause (non-spuriousness) (Shadish, Cook, and Campbell, 2002). In social science, although we

are often unable to meet all three of the criteria, especially non-spuriousness criteria, a panel data has same observations across different time points help to model the temporal sequence and build a correlation between the cause and the effect. Although less ideal, mediation analyses in social science still benefit us by providing a better understanding of a social mechanism using a well-founded theory.

To explore the mechanism between immigration and crime relationship at the neighborhood level, I use NNCS2-P, which has a sample of neighborhoods across medium to large cities in the U.S. and is inclusive of Wave 1 (1990-2001) and Wave 2 (2010-2013), available for public use through ICPSR (ICPSR 38483). The NNCS2-P data is multilevel in nature as it collects information on census tracts within the cities. Here, the neighborhood is defined by census tract and is also the unit of analysis. The original NNCS (1990-2001) contains crime and sociodemographic data for neighborhoods in 91 cities in the U.S., which had over 100,000 population in 2000. To capture the sources and consequences of changes in neighborhood crime, the NNCS2-P (P stands for panel) includes information for 2010 (2010-2013) for 8,856 census tracts in 81 cities based on the NNCS1 sample. Identical to the NNCS1, the NNCS2-P includes crime data obtained from police departments, and the sociodemographic information retrieved from the American Community Survey (ACS) 5-year estimates. NNCS2-P also collects information on foreclosures (purchased from Realty Trac) and mortgage lending from the Home Mortgage Disclosure Act. Altogether, the NNCS2-P has a sample of 8,242 census tracts across 76 cities circa 2000 and 2010 and all data are normalized to 2010 census tract boundaries (Krivo et al., 2022). In the NNCS2-P, the analytical sample of violent

crime (murder and robbery) is 7,875 census tracts across 75 cities because one city (Philadelphia, PA) did not have reliable violent crime information[3] in 1999-2000. The analytical sample for property crime is the full NNCS2-P sample of 8,242 census tracts across 76 cities. Hence, the NNCS2-P is a well-suited data set to explore the intervening process of immigrant social capital in the immigration-crime link, and the large sample of neighborhoods across the U.S. in the data strengthens the generalizability of the relationship investigated.

In this case, the panel structure of the data allows me to explore the mechanism between immigration (X) and neighborhood crime (Y) and how this relationship works through immigrant social capital (M). However, a methodological concern with utilizing data over two points (or only one-time point in the least ideal situation) to examine mediation is that it does not capture the temporal (over time) causal process inherent to the hypothesized mechanism between the explanatory variable and the outcome variable, which biases the estimates (Maxwell et al., 2011; Maxwell & Cole, 2007; O'Laughlin et al., 2018; Shrout, 2011). That is, the causal antecedent X should happen *before* the treatment, and the observed outcome should appear *after* the treatment (Baron & Kenny, 1986; Judd & Kenny, 1981). In the case of two-wave mediation analyses of immigration and neighborhood crime, the hypothesized effect of X on M could be more proximate in time than the effect of M on Y, and vice versa.

[3] Criteria for the reliability of official crime statistics is discussed in the original NNCS codebook (ICPSR 27501) (Peterson & Krivo, 2010b).

Unfortunately, it is unclear from the current literature whether the mediating effect of immigrant social capital should be happening at the same time as immigration or crime. When studying the immigration-crime relationship using the NNCS2-P, I assume that either immigration in 2000 brought about immigrant social capital in 2010 and affected crime in 2010, or that immigration in 2000 produced immigrant social capital in 2000 that influenced crime later in 2010. Although both statements and their assumptions could be either true or false, the existing knowledge does not provide any support for them.

According to the immigrant revitalization perspective, we do not know whether immigrant social capital is generated at the same time of immigration or at the same time of crime. We only know that when a neighborhood has a higher prevalence of immigrants, this neighborhood is expected to produce immigrant social capital that eventually helps to reduce crime. There is an implied temporal sequence in this revitalization process. Hence, I cannot establish the temporal order of the hypothesized relationship or consider the dynamic changes across time of the immigration-crime relationship solely using NNCS2-P. Acknowledging the limitations on casual inferences when using cross-sectional or two-wave data for mediation, additional waves of data collection can ameliorate the issue of temporal sequence in mediation analysis.

The NNCS3-P and Sample Selection

To address the major methodological concern of using panel data with two waves for mediation analyses, I collected an additional wave of data for a sub-sample of cities in the NNCS2-P – what I refer to as the NNCS3-P (pilot/panel). The

NNCS3-P sample is restricted to cities that make official crime data publicly available because crime is the outcome of the study. I start with cities because the original NNCS selected cities through stratified random sampling (within the region) of large to medium-sized cities whose police departments are willing to provide address-based crime incident data or tract-level counts of index crimes. Again, the NNCS data are multilevel in nature as it collects information on census tracts within cities.

Among the 76 cities in NNCS2-P, 20 cities have published their seven index crime data (homicide, forcible rape, robbery, aggravated assault, burglary, larceny, motor vehicle theft) on their city open data portal or their police department data portal with XY coordinates[4] of the crime incident reported to the police. Before geocoding the incidents at the census tracts level, a comparison of yearly summary statistics of each crime type for each year to the FBI-published UCR (Uniform Crime Reporting) program (Table 8: Offenses Known to Law Enforcement) yields only 18 cities have relatively reliable measures. The NNCS3 includes only the crime counts that meet the requirements as suggested in NNCS and NNCS2-P[5] and they are geocoded based on the 2010 census tract boundary.

[4] They only provide an approximate XY point within the same block instead of the exact XY coordinate.

[5] Because data from police departments cannot always be reconciled with data reported in the UCR, the following criteria were developed by the PIs of the original NNCS study to ensure data quality: (a) if the crime totaled fewer than 40 in the city for any single year (as is often the case with homicide), then tract crime counts for that year are included if the police department city crime counts differ by no more than four offenses from those reported to the FBI; (b) if the crime count totaled between 40 and 100 in the city for any single year, then tract crime counts for that year are included if the police department city crime counts are within 15 percentage points of those reported to the FBI; (c) if the crime count totaled over 100 in the city

In most cases, crimes were reliably provided from 2017 to 2021 (following the standard in footnote 2). In order to have a third wave data that is consistent with the original NNCS study that uses three-year average of crimes, I ideally would have collected data from 2019 to 2021 (if following NNCS1) or from 2020 to 2023 (following NNCS2 that uses four-year average). However, at the time of the data collection phrase of this project (summer of 2023), neither 2022 nor 2023 crime data are widely available. At the same time, the 2019-2021 period coincided with the COVID-19 pandemic, which was associated with an increase in crime (Rosenfeld & Lopez, 2022). In this case, considering data availability and adjusting for the potential influence of COVID-19 on crime, I decided to use crime data from 2017 to 2021.

It is important to note that crime data are not always available for all cities and all crime types. For the cities where crime counts for all five years were not available, I impute crime counts following the procedure used by the NNCS and NNCS2-P where the five-year count is an estimate derived from the available data. When four years of crime counts were provided, the estimate was calculated by multiplying the four-year count by 1.25. When three years of crime counts were provided, the estimate was calculated by multiplying the three-year count by 1.667. When two years of crime counts were provided, the estimate was calculated by multiplying the two-year count by 2.5. When one year of crime counts was provided, the estimate

for any single year, then tract crime counts for that year are included if the police department city crime counts are within 10 percentage points of those reported to the FBI.

was calculated by multiplying the one-year count by 5.[6] The final NNCS3-P analytical sample is 3,705 census tracts across 18 cities.

After collecting and finalizing the sample of cities that have crime data, I completed the data by obtaining sociodemographic data from the American Community Survey 2021 (2017-2021 5-year estimates) at the census tract level strictly following the NNCS procedures. The information collected includes the foreign-born population, poverty, unemployment, racial composition of the population, etc. (See NNCS2 codebook for the complete list of variables collected). To make measures comparable, I normalize the ACS 2021 data, which used the 2020 census tract boundary, to the 2010 census tract boundary[7].

Supplementing NNSC2-P, I conduct extra data collection on structural social conditions to capture the hypothesized mechanisms between immigration and neighborhood crime. These variables include family structures and local businesses from other publicly available sources (the 2000 Census, ACS 2008-2012 5-year estimates, ACS 2017-2021 5-year estimates, and Mergent Intellect) to capture different aspects of immigrant social capital. As discussed in Chapter 2, stable and multigenerational families, vivid local businesses, and increasing entrepreneurship

[6] See Appendix A which lists each city and the number of years of data that are reliably provided for each of the types of crime.

[7] To normalize the boundaries and measures, I used a data analysis tool – Tabulate Intersection – in ArcGIS Pro that computes the intersected areas of the two feature classes (census tract from two different map) and cross-tabulate the proportion of overlaying area. I then use the proportion of overlaying areas in a census tract as an areal weight to calculate the weighted population measures for all ACS 2021 variables in 2010 census tract boundary.

manifest characteristics of social organizations that produce immigrant social capital and social control – which is how immigration revitalizes communities.

First, following the data source of sociodemographic information in the original NNCS and NNCS2-P, I collect additional information on the family structure, including but not limited to household types (married, male-headed, female-headed, non-family), the population living in different types of households, subfamilies, and the percentage of co-residential grandparent households (both parents-maintained and grandparent-maintained) using summary file 3 from the 2000 Census, the 2008-2021 ACS, and the 2017-2021 ACS. I also collect business entrepreneurship information from the ACS, including the percentage of the population that is self-employed. The measurement section below will provide more discussions of the variables used.

Second, to measure entrepreneurship, I collect local small business information from Mergent Intellect by FSTE Russell, an online database that gathers worldwide business information for academic and small business researchers. In partnership with Dun & Bradstreet's private company database, Mergent Intellect provides access to private and public US and international business data. For the business in their sample, Mergent Intellect provides company information like industry, whether a manufacturing business, year of founding, revenue, the number of employees, and executive information. More importantly, their database provides addresses and geographic coordinates for the businesses so that they can be geocoded to the census tract.

Based on the NNCS2-P sample, I manually collect business information for the 76 cities. The specific information I collect is XY coordinates (latitude-longitude) of the business, which can be used to identify in which census tract the business is located, the industry sector, the year of founding, and the number of employees on site. Following Kim and Hipp (2022), I narrow the search to local businesses based on three criteria: (1) the business is not a franchise, (2) the business is neither a headquarters nor a branch, (3) and the business is a private company. I further narrow the search to consumer-facing businesses using the North American Industry Classification System (NAICS) codes. I focus on these businesses because minority-owned businesses that serve local needs are usually small and consumer-facing, and those are more likely to be places where frequent social interactions among locals happen, as discussed in Chapter 2. Here consumer-facing businesses include those in the retail, restaurant, food/drug store, and services industries (Delgado et al., 2014; Kane et al., 2017; Kim & Hipp, 2022; Porter, 2000). It is important to note that I include both active and inactive businesses to maximize the information gathered in the search because (1) there may been instances of both business closures and openings during the 20 years of the three waves data, and (2) I suspect a decent number of small businesses did not survive during the COVID-19 pandemic at the time of the search (June 2022). To properly obtain information on the number of local consumer-facing businesses in a census tract, I pinpoint the coordinates of businesses over the 2010 census tract boundary using ArcGIS Pro and then aggregated them to the census tract level. This process results in a total of 2,357 census tracts having at

least one local consumer-facing business for 2000, 2,517 for 2010, and 2,545 for 2020 in the NNCS3-P analytical sample.

Measures

I. Dependent Variables

The dependent variables are the average counts of violent crime (homicide and robbery) and burglary as a measure of property crime at the census tract level. They are three-year average crime counts for Wave 1 from 1999-2001 and Wave 2 from 2010-2013, and a five-year average for Wave 3 from 2017-2021. These are official crime data reported by the local police departments at the census tract level or incident level that were geocoded and aggregated to the census tract (Krivo et al., 2022; Peterson & Krivo, 2010b). Homicide and robbery are the most reliable measures of serious violent crime, as is burglary for property crime (Krivo et al., 2022).

II. Explanatory Variable

Immigrant Prevalence. The main independent variable is the level of immigration at the census tract level. This is an index calculated by the average of the standard scores of three measures indicative of immigration: (1) the percentage of the population that is foreign-born, (2) the percentage of the population that is foreign-born and entered the U.S. within the past ten years, and (3) the percentage of households in which no one age 14 and over speaks English very well (α for the NNCS3-P sample: 0.92 for wave 1, 0.87 for wave 2, 0.87 for wave 3). This measure is widely used in existing literature to capture the prevalence of immigration at the

neighborhood level (Krivo et al., 2022; Ousey & Kubrin, 2018; Peterson & Krivo, 2010).

III. Mediators

As shown in Figure 2, there are four mediating variables included in the analyses: two related to neighborhood family structures and two related to the local economy. These variables capture two aspects of the immigrant revitalization process – family institutions and local economies – which are also manifestations of immigrant social capital.

Family Structure

To identify both theoretically relevant and statistically reliable measures of family structures, I conduct confirmatory factor analysis (CFA) using following variables: (1) the percentage of households that are married-couple families, (2) the percentage of children under 18 years old living in married-couple families, (3) the percentage of the population who live in a family household, (4) the percentage of children under 18 years old living in households where the children are other relatives, foster children or other unrelated children to the household (reverse coded, as a measure of a disrupted family), and (5) the percentage of grandparents living with their own grandchildren under 18 years old (a measure of multigenerational family). The result of factor analysis retained two factors with factor loadings that are greater than 0.5: stable families as variable (1) and (2), and (1) and (3). Because (1) and (3) are technically measuring the same thing but in different universe (one is households and the other is population), I decided to use (1) and (2) to capture stable

family. Although CFA shows that (5) does not belong to the concept of stable family, (5) itself has relatively high uniqueness (0.6) that I decided to use this as a standalone measure of multigenerational family given theoretical relevancy. The details of these two main measures of family structure will be described below.

Stable family. This standardized scale captures the level of a stable family environment in the neighborhood. This consists of two variables: (1) the percentage of households that are married-couple families, and (2) the percentage of children under 18 years old living in married-couple families ($\alpha = 0.783$).

Multigenerational Family. This variable measures the population 30 years and over who are grandparents and live with their own grandchildren under 18 years old (regardless of whether the grandparent is responsible for the grandchildren or not). Due to the uniqueness of this measure in the CFA and theoretical relevancy, I decided to use this single measure as a proxy for multigenerational families, aiming to capture the extensiveness of the family structure and the presence of grandparents in a family.

It is important to note that this measure may not accurately capture multigenerational families. The current measure may cover two scenarios: (1) children living with their parents and grandparents in the same housing unit or (2) children living with their grandparents in the same housing unit without their parents. So if the measure only capture scenario (2) in reality, then this variable do not measure multigenerational family but skipped generation family. Moreover, under scenario (2), it is possible that children living with their grandparents AND other relatives (such as aunts/uncles and their children) in the same household (scenario

(2b)), but they are not necessarily the same family. According to the Census, household indicates people who occupying a same unit, while family is people living in the same household that are related by birth, marriage, or adoption. So in scenario 2(b), there are two families, one for the grandchildren and the grandparent and the other for the uncles/aunts and their children, but one household because they living in the same housing unit. These different scenarios indicate the board coverage of family structures when using this measures and I may or may not correctly capture multigenerational families. The implications of these limitations and findings will be discussed in Chapter 5.

Local economy

Self-employment. This variable is the percentage of the population 16 years and over who were self-employed in either their own incorporated or non-incorporated business. This measure is a proxy for the level of entrepreneurship at the neighborhood level, and this measure has been used to capture ethnic entrepreneurship in the prior study (Chacko & Price, 2015; Price & Chacko, 2009).

Local consumer-facing businesses (Business). This variable is the rate of local consumer-facing businesses per 1000 people in the neighborhoods in a given year (2000, 2010, and 2020 in this study).[8] It is calculated as the number of

[8] Mergent Intellect provides information on the year of establishment of the businesses, and I used this information to calculate whether a business is located in the neighborhood at a given time point. However, since about 50% of the companies have missing information on years of establishment, I only use the businesses with years of establishment information. Further sensitivity analyses of including businesses without time of establishment information are also conducted. The results of the model remain unchanged.

businesses in a census tract divided by the population, multiplied by 1000. Utilizing information from Mergent Intellect, a business is considered local when it is a privately owned company that is not a franchise, neither a headquarters nor a branch of a company (Kim & Hipp, 2022). Among these local businesses, only businesses belonging to consumer-facing industries were collected because these are the places where social interaction among residents is most likely to occur (Delgado et al., 2014; Kane et al., 2017; Porter, 2000). Following Kim and Hipp (2022), I use the six-digit NAICS codes[9] to categorize consumer-facing businesses that fall into three general domains: Retail (Apparel, General Merchandise, Home Products, Personal Products, and Specialty); Restaurants and Food/Drug stores (Convenience Stores, Drug Stores, Groceries, and Specialty Food); and Services (Auto Services, Childcare Services, Gas Stations, Laundry, Hair Care Services, Other Personal Services, and Repair Services).

IV. Control Variables

To isolate the influence of immigration on neighborhood crime, I control for a number of neighborhood-level variables that are found to be both theoretically and

[9] Here is the list of 6-digit NAICS codes that classified as consumer facing business according to Kim & Hipp (2022): Retail: (448110, 448120, 448130, 448140, 448150, 448190, 448210, 452111, 452112, 452910, 452990, 453310, 453210, 443141, 442110, 442210, 442291, 442299, 444210, 444220, 444130, 444110, 444120, 444190, 453991, 446120, 446199, 453910, 453998, 451211, 451212, 443142, 451140, 451110, 451120, 446130, 453220, 453110, 448310, 448320, 451130); Restaurants: (722511, 722514, 722515, 722513); Food/Drug Stores: (445120, 446110, 445110, 311811, 445210, 445220, 445230, 445291, 445292, 445299, 446191); Services: (532111, 441310, 441320, 811111, 811112, 811113, 811118, 811121, 811122, 488410, 811191, 811192, 811198, 624410, 447110, 447190, 812320, 812310, 611511, 812111, 812112, 812113, 532220, 532299, 541940, 812191, 812199, 812910, 812990, 541921, 812921, 812922, 561622, 811212).

empirically important to the neighborhood level of crime (Kubrin & Desmond, 2015; Lyons et al., 2022; Peterson & Krivo, 2010a; Sampson & Groves, 1989; Shaw & McKay, 1942).

Neighborhood disadvantage. This variable is an index that combines the average of the standardized scores of six variables: joblessness (percentage of the population aged 16-64 who are unemployed or not in the labor force), professional workers (percentage of employed population aged 16 and over works in management, business, and related occupations, reversed coded), the percentage of adults (25 years old and older) who were high school graduates (reverse coded), the percentage of households that were female-headed families, secondary sector workers (percentage of the employed population aged 16 and older that works in the six occupations with the lowest average incomes), and poverty rate. The alpha level for the NNCS3-P sample is 0.92 for wave 1, 0.90 for wave 2, 0.89 for wave 3.

Residential instability. This variable is an index that uses the average scores for two variables: the percentage of the housing units that were renters occupied and the percentage of the population (five years old and older) who lived in a different house five years ago.

Vacancy. This measure is the percentage of vacant housing units.

Foreclosures. The foreclosure rate is calculated with the five-year average (2017-2021)[10] of the number of foreclosures per 100 housing units (Baumer et al., 2012; Lyons et al., 2022). This measure is derived from proprietary data on all

[10] Respectively, a three-year average of 1999 to 2001 was used for wave 1 and 2010 to 2013 for wave 2.

individual mortgage foreclosure transactions from 1998 to 2015[11] that were purchased from RealtyTrac as part of the NNCS2. For data from 2017-2021, the estimate is produced by conducting linear interpolation using yearly data from 1998-2015 and the *ipolate* function in Stata17.

Demographics. I included two demographic characteristics: percent young males and the ethno-racial neighborhood types that reflect racial segregation (Peterson & Krivo, 2010; Krivo et al., 2021). Percent young males is the percentage of young males in the population that are between the ages of 15 and 34 years old. There are five ethno-racial neighborhood types: White, African American, Latino, Minority, and Integrated. In each wave, a neighborhood is characterized as a specific ethno-racial type (White, African American, and Latino) when at least 70% of the tract population is comprised of that ethno-racial type. In the case of minority neighborhoods, they comprise at least 70% African American and Latino residents, while neither of these groups independently reach the 70% threshold. Finally, the remaining neighborhoods are multi-ethnic neighborhoods that have any other ethnic-racial combination that is not the groups above.

Spatial proximity. I control for crime levels in the nearby neighborhoods by including spatial lags of violent crime and burglary rates in the models (Lyons et al., 2022). The spatial weights were calculated using the spatial contiguity matrix based on the first-order queen criterion, meaning census tracts that share any boundaries (edges and corners) were defined as neighbors.

[11] The foreclosure that from 2016 to 2021 is extrapolated based on data from 1998 to 2015.

Analytical Strategy

The mediation analyses proceed in three steps. First, I seek to establish the empirical relationship between immigration and neighborhood crime, both cross-sectionally and longitudinally, to provide a baseline understanding of the relationship. Figure 2 demonstrates simplified measurement models of mediation analyses. Step 1 assesses the relationship between immigrant prevalence on neighborhood crime, the *c* path indicated in Figure 2, without considering immigrant social capital. This step aims to fulfill the criteria of demonstrating the association between the potential cause (immigration) and the effect (neighborhood crime) when making causal inferences. The analyses in this step also aim to establish the relationship to be mediated following Baron and Kenny (1986).

Although longitudinal analysis is ideal for mediation analyses, I specifically also show the immigration and crime relationship cross-sectionally in three waves (1999-2001, 2010-2013, 2017-2021) because the sample has changed between waves. As the NNCS3-P only has 18 cities from NNCS2-P, the observed relationship could be unique to the cities that are available in NNCS3-P. For example, the immigration-crime correlation may differ when looking at neighborhoods in 18 cities and neighborhoods in 76 cities in 2010. Descriptively, on average the NNCS3-P sample has a slightly more violent crime and less burglary compared to the NNCS2-P sample. The neighborhoods in NNCS3-P also have a higher prevalence of immigrants, less stable families, marginally more multigenerational families, local businesses, and self-employment[12]. In Chapter 4, I will discuss how the immigration-

[12] See Appendix B for more descriptive comparisons of the two samples.

crime relationship at the neighborhood level differs in three different waves when using different samples in detail, and potential explanations for the differences. In sum, step 1 analyses help us to obtain a comprehensive image of the immigration-crime nexus over time descriptively.

After establishing the relationship to be mediated in step 1, the second and the third step examines the pathways of mediation through two sets of analyses as shown in Figure 3: (1) the effect of immigration on immigrant social capital (path *a*) and (2) the effect of immigration social capital on neighborhood crime (path *b*).

In the fourth step, I will test whether immigrant social capital mediates the immigration-crime link (indicated as the dash-doted lines in Figure 3) as theorized in two ways: (1) fixed effect panel data analyses and (2) temporally ordered mediation analyses. This step is shown in Figure 3. Different previous steps, this step examines the direct effect of immigrant prevalence on neighborhood crime (path *c'* in) controlling for immigrant social capital and the indirect effect of immigration on crime through immigrant social capital (path *a* and *b*). All three steps of the analytical strategy build upon each other and are geared toward providing a comprehensive understanding of how immigration shapes crime via immigrant social capital as captured by stable families, intergenerational families, businesses, and self-employment.

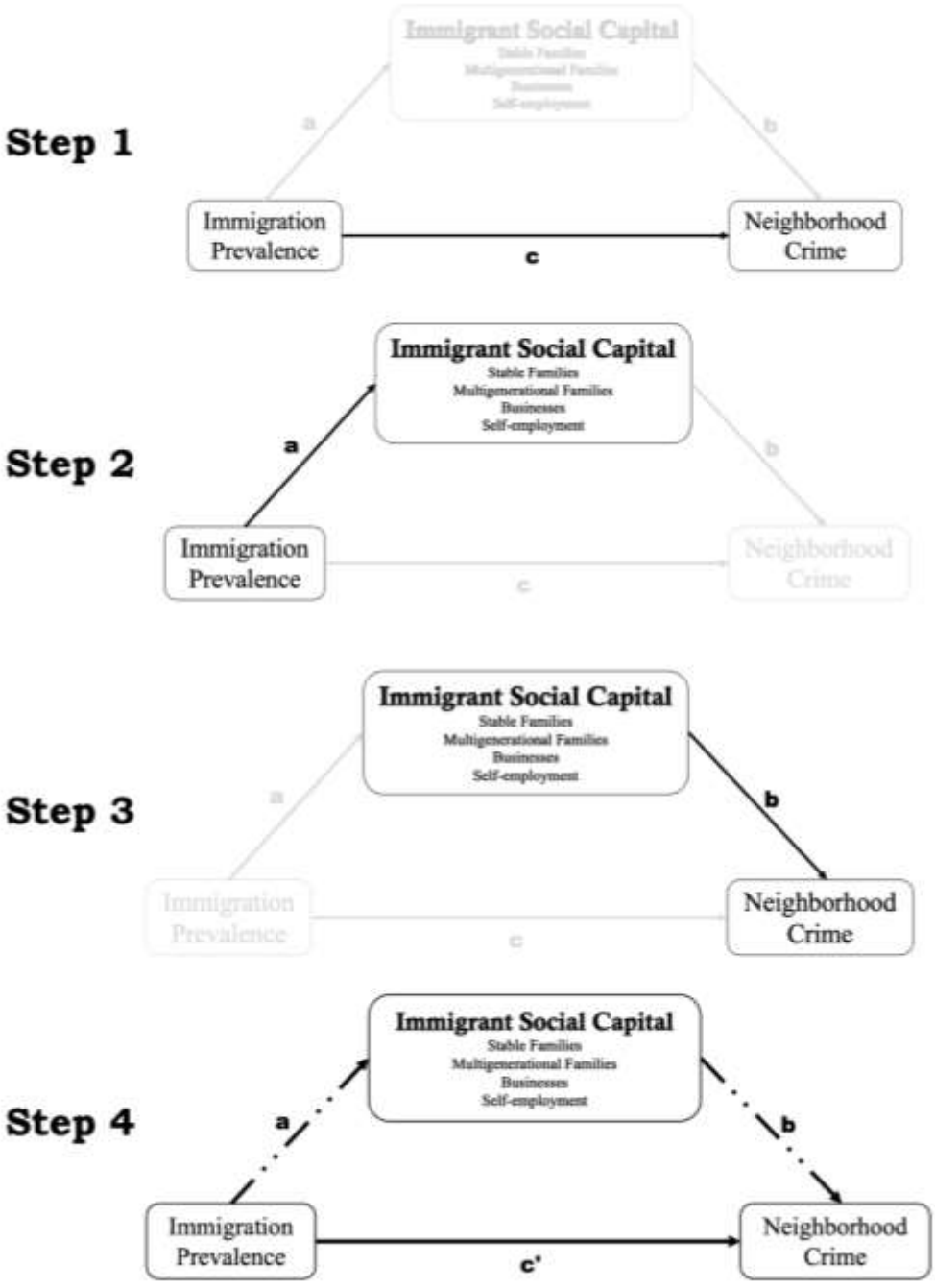

Figure 3. Measurement models to establish mediation model by steps
(Solid lines denote direct pathways; Dash-dot lines denote indirect pathways through another variable).

I. The Immigration-Crime Relationship at Three-time Points (Cross-sectional)

To examine and establish the baseline relationship between immigration and crime for each wave, I estimate Poisson models for violent crime and burglary counts. Both violent crime and burglary counts are highly left-skewed since most neighborhoods have zero violent crime or burglary in each wave. Tests for non-normality and heteroscedasticity in the residuals' distributions suggest the usage of generalized linear regressions of Poisson distribution with robust standard errors. I also specify the outcomes with tract population as exposure, which makes the interpretation of crime counts into crime rates across neighborhoods (Osgood, 2000). Lastly, cities dummies are included in the regression and the standard errors are clustered at the city level to account for unobserved city-specific characteristics related to immigration or crime, which is basically fixed effect model. Clustering at the city level also accounts for intra-city correlation[13] as the neighborhoods spatially are nested within cities and the cities are the units that were first selected for the NNCS sample, then the census tracts of the cities[14].

In this step, there are two sets of analyses. The first set of models examines the influence of immigration on violent crime and burglary separately for each wave of the panel data (Wave 1 in 1999-2001, Wave 2 in 2010-2013, and Wave 3 in 2017-2021) based on the NNCS3-P sample (3,705 census tracts within 18 cities). The

[13] Simple multilevel models of immigration on crime show statistically significant intra-class correlation coefficient of 0.2 for violent crime and 0.3 for burglary.
[14] The NNCS codebook (Peterson & Krivo, 2010) for the first wave details how the original NNCS sample was selected.

second set of analyses runs the same models using different samples, in that the immigration-crime link at Wave 1 and Wave 2 will be using the larger NNSCS-P sample (8,242 census tracts within 76 cities) and at Wave 3 will be using the NNCS3-P sample.

$$Crime_i = \beta_{i0} + \beta_1 Immigrant\ Prevalence_i + \beta_{2,3,\ldots 8} Controls_{(2-8)i} + \sum_{l=1}^{17} \beta_{CityID_l} CityID_i + \epsilon_i \quad (1)$$

Equation (1) shows the mathematical model of the regressions for the NNCS3-P sample. Crime is the dependent variable for individual tract *i*. β_0 is the intercept. β_1 through β_8 are the coefficients for the explanatory variable and covariates at the tract level. $\sum_{l=1}^{17} \beta_{CityID_l} CityID_i$ represents the effect of city-specific dummies. ϵ_i is the error term for individual tract *i*. The same regression is applied to each wave for the cross-sectional model.

II. Pre-mediation: Establishing Pathways of Mediation Models

According to Baron and Kenny (1986), it is essential to establish the "causal pathways" of variables of interest before examining the intervening variable that mediate the relationship. Using the NNCS3-P data, I conduct longitudinal data analyses on the immigration-crime link by estimating multilevel Poisson regressions with city-level random intercept. I use multilevel models[15] because NNCS3-P is a

[15] As discussed earlier, it is important to have standard errors clustered at the city level to account for unobserved city-specific characteristics and accounts for intra-city correlation. However, the *xt*-regression models in Stata17 do not allow for a fixed

multilevel data, which is a sample of census tracts (level 1) nested within the cities (level 2). A multilevel random intercept model with city dummy variables adjusted for neighborhood clustering within cities, and it produces the same coefficients and significance level as a fixed effect model (Lyons et al., 2022). Hence, I estimate random intercept for the city to account for the substantial variation of crimes across cities and to appropriately consider the multilevel nature of the data. Different from the cross-sectional models in the first step, the multilevel models capture the changes over time in the neighborhoods while also accounting for the clustering of census tracts within cities. I will first investigate the relationship between immigration and crime without considering immigrant social capital.

$$Crime_{ijt} = \beta_{0ijt} + \beta_1 Immigrant\ Prevalence_{ijt} + \beta_{2,3,\dots 7} Controls_{(2-7)ijt} + \sum_{t=1}^{2} \beta Year_{ij} + \sum_{l=1}^{17} \beta_{CityID_l} CityID + \epsilon_{ijt} \quad (2)$$
$$\beta_{0j} = \gamma_{00} + u_{0j}$$

Different from equation (1), the cross-sectional immigration-crime regression, crime is the dependent variable for **individual tract *i* in city *j* at wave *t*.** β_{0j} is the random intercept specific to each city *j*. β_1 through β_7 are the coefficients for the explanatory variable and covariates at the tract level for each wave *t*. β_{year_t} are the coefficients for the wave/year dummies (2000, 2010, 2020 respectively for each wave) to adjust for wave-specific effects due to the long time (about 10 years)

effect model that considers city variation. When running *xt*-regression models, the city-level dummies are omitted, and the function would not allow me to cluster the standard error at the city level. Thus, I use multilevel models with city random intercept, city dummies, and year dummies to produce similar estimates as the *xt*-regression models.

between waves. ϵ_{ij} is the error term for individual tract *i* in city *j* at wave *t*. γ_{00} is the fixed effect intercept at the city level, and u_{0j} is the city-specific random effect for the intercept.

Second, I estimate another set of multilevel models of immigrant prevalence on each of the mediators to predict the effect of immigration on immigrant social capital (path *a* in Figure 2). All models are estimating linear regressions. Equation (3) presents the mathematical models for the theoretical model shown in Figure 2, and the same model will be employed for each of the mediators individually. Immigrant social capital, measured separately by stable family, intergenerational family, customer-facing local business, and self-employment, is the dependent variable for individual tract *i* in city *j* at wave *t*. All other notations stay the same.

$$\begin{aligned} Immigrant\ Social\ Capital_{ijt} \\ &= \beta_{0ijt} + \beta_1 Immigrant\ Prevalence_{ijt} \\ &+ \beta_{2,3,\dots 7} Controls_{(2-7)ijt} + \sum_{t=1}^{2} \beta Year_{ij} \\ &+ \sum_{l=1}^{17} \beta_{CityID_l} CityID + \epsilon_{ijt} \\ \beta_{0j} &= \gamma_{00} + u_{0j} \end{aligned} \tag{3}$$

Lastly, I investigate the influence of each immigrant social capital measure on neighborhood crime (path *b* in Figure 2). Similar to the previous analyses, I estimate multilevel Poisson regressions with city random intercept of stable families, intergenerational families, customer-facing local businesses, and self-employment on crime individually.

$$
\begin{aligned}
Crime_{ijt} = \ & \beta_{0ijt} + \beta_1 Immigrant\ Social\ Capital_{ijt} \\
& + \beta_{2,3,\dots 7} Controls_{(2-7)ijt} + \sum_{t=1}^{2} \beta Year_{ij} \\
& + \sum_{l=1}^{17} \beta_{CityID_l} CityID + \epsilon_{ijt} \\
\beta_{0j} = \ & \gamma_{00} + u_{0j}
\end{aligned}
\tag{4}
$$

III. The Role of Immigration Social Capital in the Immigration-Crime Nexus

To examine the intervening role of immigrant social capital on the immigration-crime relationship, I examine the mediation effect of immigrant social capital through (1) fixed effect panel data analyses and (2) temporally ordered mediation analyses using generalized structural equation modeling (GSEM).

GSEM is the generalized version of traditional SEM. GSEM (as well as SEM) is not a specific regression model, but an approach to model estimation. In this case, many different types of analyses are within the sphere of SEM, including but not limited to linear regression, path analysis, and confirmatory factor analyses. Here, I am using GSEM because of the nature of the dependent variables, counts of crime events within census tracts, and the complex data structures, which are multilevel panel data of census tracts within cities. When conducting mediation analysis, GSEM/SEM allows us to specify, estimate, and test the direct and indirect (mediation) effects in a single model (Hayes, 2017; Iacobucci, 2008; MacKinnon et al., 2002). GSEM/SEM also can estimate multiple mediation paths simultaneously (Iacobucci, 2008), which is crucial as this study is investigating different aspects of a mediating mechanism – immigrant social capital.

While GSEM is the mathematical machinery to examine the direct and indirect effects of a relationship, it is also important to articulate the underlying causal assumptions of the relationship to produce any causal inferences (Pear, 2009). In this study, I argue the presence of a higher prevalence of immigration "causes" lower levels of crime at the neighborhood level. This relationship is being tested based on the following assumptions. First, immigration does not influence neighborhood crime directly but rather indirectly through immigrant social capital (stable families, multigenerational families, local businesses, self-employment). When putting this assumption in a potential outcomes framework, it means:

- Neighborhoods with a high prevalence of immigration will have a high presence of immigrant social capital, thus less crime, and
- Neighborhoods with a low prevalence of immigration will have low presence of immigrant social capital, thus more crime.

Second, I assume that unobserved confounders such as immigration policies and police activities that influence immigrant social capital and crime will not influence immigration. When these assumptions are true, the observed direct and indirect effect of immigration on crime can be interpreted casually. However, I will preserve caution when making casual inferences because these assumptions may not be true as (1) there are possible unobserved confounders that influence immigration, immigrant social capital, and neighborhood crime that are not observed with the existing data and (2) immigration does have a direct influence on crime not through immigration social capital (which will be shown in Chapter 4).

Fixed effects model

First, using multilevel random intercept models with city dummy variables in a panel dataset, which again resemble fixed effect models (Lyons et al., 2022), I investigate how changes in immigrant prevalence over time affect changes in crime at a later wave, with the mediators (stable family, intergenerational family, customer-facing local business, and self-employment) potentially explaining part of that relationship. Specifically, I examine the role of immigrant social capital in the immigration-crime relationship by (1a) first NOT controlling for immigrant social capital measures in the model and then (1b) investing how the immigration-crime relationship changed after controlling for immigrant social capital in the regression.

This approach allows us to explore longitudinal relationships and helps us to understand the dynamics of the immigration-crime nexus without strictly enforcing the temporal sequence of a relationship. As immigration and neighborhood crime have a dynamic relationship (Martinez et al., 2010), the advantage of fixed effect models is that they remove observed time-invariant neighborhood-specific characteristics so we can assess the net effect of immigrant prevalence on neighborhood crime. Especially since the entire study period for three waves is as long as thirty years, there may be unobserved factors that play a role in the immigration-crime relationship that we are not able to capture in the data.

Equation (2) in the second step has examined the immigration-crime relationship without considering immigration social capital. When considering the role of immigrant social capital, those measures will be included and be controlled for, one by one and altogether, in the regression.

$$
\begin{aligned}
Crime_{ijt} = \ & \beta_{0ijt} + \beta_1 Immigrant\ Prevalence_{ijt} \\
& + \beta_{2,3,\dots 7} Controls_{(2-7)ijt} \\
& + \beta_{8,9,10,11} Immigrant\ Social\ Capital_{(8-11)ijt} \\
& + \sum_{t=1}^{2} \beta Year_{ij} + \sum_{l=1}^{17} \beta_{CityID_l} CityID + \epsilon_{ijt} \\
& \beta_{0j} = \gamma_{00} + u_{0j}
\end{aligned}
\tag{5}
$$

Temporally ordered mediation analyses

However, fixed effect models have their own limitation when testing the immigrant revitalization perspective. When estimating fixed effect models, I am assuming the temporal sequence of immigrant prevalence to immigrant social capital to neighborhood crime WITHOUT specifying the timing of these measures in the model. In this case, the "direction" of the relationship is buried. If I observed a significant association between changes in immigrant prevalence and changes in crime, it would be the "effect" of immigration on crime, NOT the "effect" of crime on immigration solely because of the theoretical assumptions proposed to be examined – the immigrant revitalization perspective.

Acknowledging temporal ordering is necessary for causal inference (that is, the causal antecedent X should happen before treatment) and the observed outcome should appear after the treatment (Baron & Kenny, 1986; Judd & Kenny, 1981), it is necessary to conduct temporally ordered mediation analyses. For the final set of analyses, I estimate how immigrant prevalence at Wave 1 (1990-2001) influences immigrant social capital at Wave 2 (2010-2013) and in turn, affects neighborhood crime at Wave 3 (2017-2021) by strictly enforcing the timing of the investigating mechanism in GSEM. Different from the fixed effect models, this specification of sequential ordering in GSEM examines the causal pathway from immigrant

prevalence to immigrant social capital to crime over time, instead of assuming such temporal order and direction of the relationship.

We need to navigate the temporal ordered models with caution as the sample size in these analyses is shrunk because there is only one complete causal pathway to analyze. Figure 4 is a typical statistical analysis model of mediation analyses using three waves of longitudinal data (Little, 2013). Again, X is the independent variable, M is the mediator, Y is the dependent variable, and the number indicates the temporal sequence of the variables. As shown in the figure, there is only one complete path that is temporally ordered, X1 → M2 → Y3, when considering temporal sequence in a three-wave panel data. When applying this figure to the analyses in this study, only 3,705 census tracts (one-third of 11,115 census tracts in the panel data) have information on immigration at time 1, immigrant social capital at time 2, AND crime at time 3. Thus, the results of the GSEM model will be derived from only these census tracts that have information for three time points.

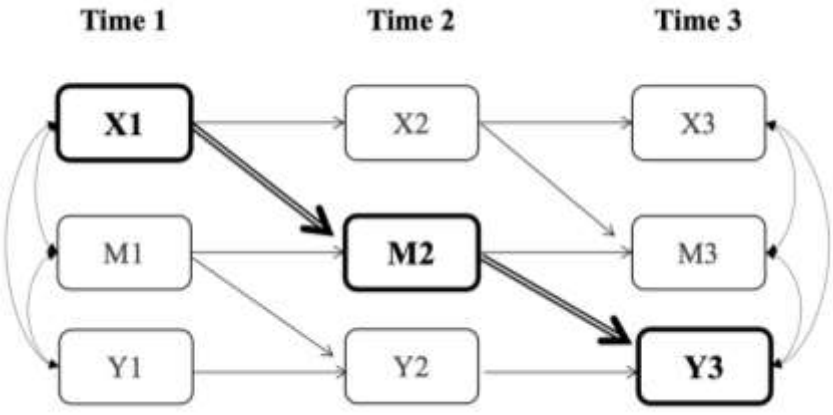

Figure 4. Statistical analysis model of longitudinal mediation model using structural equation modeling adopted from Little (2013).

Despite the limitation, this approach still provides a more nuanced understanding of the temporal order of the relationships between immigration and neighborhood crime and tests the immigrant revitalization perspective more precisely. The models predicting crime use Poisson regressions, and the models predicting other mediators use linear regressions. All the equations include city-specific dummies and year-specific dummies, which resemble a fixed-effect Poisson model for tracts within cities over time. Again, the standard errors are clustered at the city level. Instead of running traditional panel regression, such as *xt-regressions* in Stata, this is the only way to produce similar estimates for fixed-effect Poisson model for mediation analyses and accounting for the multilevel nature of the data when using GSEM in Stata because *xt-regressions* are not compatible in the GSEM function.

Equation (6) presents the mathematical temporal ordered mediation model for the stable families, as an example. I examine each of the mediators similarly.

$$\begin{aligned} Crime_{ijt} = {} & \beta_{0ijt} + \beta_1 Stable\ Family_{ijt-1} \\ & + \beta_2 Immigrant\ Prevalence_{ijt-2} \\ & + \beta_{3,4,\dots 9} Controls_{(3-9)ijt} + \sum_{t=1}^{2} \beta Year_{ij} \\ & + \sum_{l=1}^{17} \beta_{CityID_l} CityID + u_{ijt} \end{aligned} \tag{6-1}$$

$$\begin{aligned} Stable\ Family_{ijt-1} & \\ = {} & \gamma_{0ijt-1} + \gamma_1 Immigrant\ Prevalence_{ijt-2} \\ & + \gamma_{2,3,\dots 8} Controls_{(2-8)ijt} + \sum_{t=1}^{2} \gamma Year_{ij} \\ & + \sum_{l=1}^{17} \gamma_{CityID_l} CityID_i + v_{ijt} \end{aligned} \tag{6-2}$$

I construct the above equations following the Stata manual in that a mediation model is completed by at least two equations: (1) predicting the influence of the independent variable and the mediator on the dependent variable, and (2) predicting the effect of the independent variable on the mediator.[16] Unlike SEM, GSEM in Stata does not allow post-estimation for direct or indirect effects. However, we can calculate the indirect and total effects by using *nlcom.* Using the sample example for the stable family, the indirect effect and total effect is calculated by:

Indirect effect of Stable Family = $\beta_1\gamma_1$

Total effect accounting for Stable Family = $\beta_2 + \beta_1\gamma_1$

Where

β_1 = *path coefficient for Stable Family* → *Crime*

γ_1 = *path coefficient for Immigrant Prevalence* → *Stable Family*

β_2 = *path coefficient for Immigrant Prevalence* → *Crime*

Then, I mediated all aspects of immigrant social capital one by one to understand how they intervene in the immigration-crime relationship as a group of working mechanisms. For instance, the first model of this set of analyses starts with regression within only one mediator – stable families. The second regression will have two mediators, both stable families and intergenerational families, and so on. The last regression in this set of analyses will include all four mediators in the model.

To examine the total indirect effect when all mediators are considered, I calculate the following equations and obtain the indirect and total effects through the same

[16] https://www.stata.com/manuals/semexample42g.pdf

method above. The total indirect effect when specifying multiple mediators will be the sum of individual indirect effects for each mediator, and the total effect when accounting for multiple mediators is calculated by the sum of the direct effect of immigrant prevalence on crime and the total indirect effects.

$$\begin{aligned} Crime_{ijt} = {} & \beta_{0ijt} + \beta_1 Stable\ Family_{ijt-1} \\ & + \beta_2 Immigrant\ Prevalence_{ijt-2} \\ & + \beta_{3,4,\dots 9} Controls_{(3-9)ijt} + \sum_{t=1}^{2} \beta Year_{ij} \\ & + \sum_{l=1}^{17} \beta_{CityID_l} CityID + u_{ijt} \end{aligned} \tag{7-1}$$

$$\begin{aligned} Stable\ Family_{ijt-1} = {} & \gamma_{0ijt-1} + \gamma_1 Immigrant\ Prevalence_{ijt-2} \\ & + \gamma_{2,3,\dots 8} Controls_{(2-8)ijt} + \sum_{t=1}^{2} \gamma Year_{ij} \\ & + \sum_{l=1}^{17} \gamma_{CityID_l} CityID + v_{ijt} \end{aligned} \tag{7-2}$$

$$\begin{aligned} Intergenerational\ Family_{ijt-1} = {} & \delta_{0ijt-1} + \delta_1 Immigrant\ Prevalence_{ijt-2} \\ & + \delta_{2,3,\dots 8} Controls_{(2-8)ijt} + \sum_{t=1}^{2} \delta Year_{ij} \\ & + \sum_{l=1}^{17} \delta_{CityID_l} CityID + \eta_{ijt} \end{aligned} \tag{7-3}$$

$$\begin{aligned} CFLB_{ijt-1} = {} & \vartheta_{0ijt-1} + \vartheta_1 Immigrant\ Prevalence_{ijt-2} \\ & + \vartheta_{2,3,\dots 8} Controls_{(2-8)ijt} + \sum_{t=1}^{2} \vartheta Year_{ij} \\ & + \sum_{l=1}^{17} \vartheta_{CityID_l} CityID + \zeta_{ijt} \end{aligned} \tag{7-4}$$

$$\begin{aligned} Self\ Employment_{ijt-1} = {} & \kappa_{0ijt-1} + \kappa_1 Immigrant\ Prevalence_{ijt-2} \\ & + \kappa_{2,3,\dots 8} Controls_{(2-8)ijt} + \sum_{t=1}^{2} \kappa Year_{ijt} \\ & + \sum_{l=1}^{17} \kappa_{CityID_l} CityID + \theta_{ijt} \end{aligned} \tag{7-5}$$

Chapter 4: Results

Descriptive Statistics

Table 1 reports descriptive statistics for all variables used in the analyses across the three waves for the NNCS3-P sample. Across the 18 cities in NNCS3-P, an average neighborhood in this sample has about seven violent crimes and 18 burglary incidents at Wave 3. These numbers are the lowest of the past two decades. An average neighborhood had the highest level of crime at Wave 1 around the early 2000s and has decreased since then. This declining crime trend for both violent crime and burglary is parallel with the great crime decline since the late 1990s in the U.S. (Sharkey, 2019; Zimring, 2008).

On the other hand, the components of the immigrant prevalence index show a relatively stable trend of immigration. An average neighborhood has about 20 percent foreign-born residents, 10 percent newly arrived immigrants, and linguistically isolated households across the NNCS3-P. Surprisingly, the neighborhoods of NNCS3-P do not resemble the increasing immigration trend in the country. This could be due to those eight out of the 18 cities in the NNCS3-P which experienced lower than national average foreign-born population growth from 2000 to 2015 (Singer, 2004, 2015). Despite the static trends of immigration in this sample on average, there is still great variation among them. The range of the immigrant prevalence components indicates that while some neighborhoods have about 80 percent foreign-born population and are severely linguistically isolated, others have

no immigration at all. Lastly, there was a small decrease in new immigrants during the 2010s and less linguistically isolated households around the 2020s.

On immigrant social capital: first, the family structure of neighborhoods in the sample has become slightly less stable over the past two decades. The decline of stable families mostly happened between 2000 and 2010. The range of stable family components indicates that there are neighborhoods that have extremely stable family conditions while others are not as stable. In this sample, an average neighborhood has about 35% of the households are married-couple families and 60% of children are living in a married-couple family across the tree waves. The distribution of the stable family index components demonstrated that while some neighborhoods have as little as one percent married-couple families[17] and no children are living in a married-couple, other neighborhoods have a very high prevalence of married-couple families (up to 90%) and almost all children are living in married-couple families.

In contrast, multigenerational families are much less prevalent in our neighborhoods. In this sample, only about 4% of grandparents are living with their grandchildren. There has been a 5% increase in the share of the population living in multigenerational households in the U.S. since 2001 (Cohn et al., 2022), while multigenerational families in the NNCS3-P sample have decreased for the past 20 years. Again, there are neighborhoods with no multigenerational households, while some neighborhoods have up to 35%.

[17] There are four census tracts (one from Wave 1 and Wave 2, and two from Wave 3) that are excluded in this description because they do not have any married-couple family and they are all tracts located in the city center.

At the same time, the pervasiveness of consumer-facing local businesses and self-employment increased from 2000 to 2020. An average neighborhood had only two consumer-facing local businesses per capita in the 2000s but increased to six in the 2020s. The neighborhoods in the sample have considerable variation in the presence of consumer-facing local businesses. For example, at Wave 3, while some neighborhoods have a rate of 153 businesses per 1000 people, others have no consumer-facing local businesses. However, this divergent distribution is anticipated given we expect these local small businesses to be concentrated in certain areas that serve locals. Likewise, about 10% of the population in the NNCS3-P neighborhoods are self-employed. Again, while some neighborhoods have no self-employed residents, others have populations that are as much as 75% self-employed (peaked at wave 2), indicating the prevalence of entrepreneurship living in some areas.

In terms of socio-demographics, the average level of neighborhood disadvantage, residential instability, foreclosure rate, and vacant housing increased from 2000 to 2020. There are fewer majority White or African American neighborhoods and marginally more Hispanic and minority neighborhoods in recent years. Notably, there is about a 10% increase in the number of multi-ethnic neighborhoods in this sample of U.S. cities. The distributions of these socio-demographics demonstrate considerable variations in socioeconomic and housing conditions across the neighborhoods in the sample.

Cross-sectional Analyses of Immigration-Crime Relationship

Table 2a presents an initial investigation of the association between immigrant prevalence and crime counts cross-sectionally for the three waves individually. The

goal here is to provide a detailed understanding of the immigration-crime relationship at three different time points and to help understand and interpret findings in the panel data analyses. Presenting data from the NNCS3-P, Table 2a reveals that immigration has a null effect on violent crime at Wave 1 and Wave 2 but significantly increases violent crime at Wave 3. On the other hand, immigration significantly reduces burglary regardless of the time period. It is important to note that the null effects, with negative coefficients, found for violent crime in the first two waves of data are consistent with previous literature (Ousey & Kubrin, 2018), but the significant positive relationship between immigration and violent crime is surprising.

According to Baron and Kenny (1986), the most essential step of mediation analysis is to establish the relationship between the causal variable and the outcome, which is that immigration is statistically associated with violent crime. This is based on the argument that a relationship needs to exist to be mediated. Although immigration does not statistically predict violent crime for Wave 1 and Wave 2, immigration does statistically predict violent crime at Wave 3 and all waves for burglary.

To further solidify the baseline relationship between immigration and crime, especially for violent crime, I argue the null findings could be the result of sample changes across waves. As a reminder, the NNCS3-P has 18 cities from the original NNCS2-P, which has 76 cities. Table 2b shows the influence of immigrant prevalence on crime for Wave 1 and Wave 2 using the full NNCS2-P sample (8,242 census tracts across 76 cities; 7,875 census tracts across 75 cities for violent crime in Wave 1 due to missing data on homicide and robbery).

As demonstrated in the violent crime model for Wave 1, the association between immigrant prevalence and crime is negative and statistically significant, which is consistent with earlier studies using the NNCS1 (Peterson & Krivo, 2010a). For the burglary models, the relationship stays negative and significant regardless of the time period and sample size. Although the immigration-violent crime relationship stays null for Wave 2, an existing study using the NNCS2 Cross-sectional found that immigrant prevalence significantly reduces violent crime (Krivo et al., 2021). This difference could be due to the different sample sizes between NNCS2-P and NNCS2 Cross-sectional, as NNCS2 Cross-sectional data have 85 cities while the NNCS2-P have 76 cities.

The difference of nine cities between NNCS2 Cross-sectional and NNCS2-P matters in the context of the inconsistent finding of immigration-crime association, where the immigration-crime nexus is often conditioned on city context. Among the nine cities not included in NNCS2-P, seven of them are gateway cities. In the literature on immigrant gateway cities – cities with a long history of immigrant settlement and a higher-than-average immigrant population (Singer, 2004), existing studies show that city context matters in that the immigrant communities are more likely to produce a protective influence on reducing crime in gateway cities than neighborhoods in non-gateway cities (For example, see Harris & Feldmeyer, 2013; Painter-Davis, 2016; Ramey, 2013). Although the city context is not the central focus of this dissertation, it is necessary to acknowledge its importance especially when we observe different relationships across samples. In this case, I suspect the null immigration-violent crime relationship when using the panel data could be due to

losing about 1,400 census tracts from the seven gateway cities in the cross-sectional data which are most likely to receive the protective influence of immigration on crime.

Even if the immigration-violent crime relationship is truly null, some scholars suggest that, against Baron and Kenny's method, an insignificant relationship between X and Y should not be the "gatekeeper" for tests for mediation, especially when a relationship is built on a theoretically sound hypothesis (Zhao et al., 2010). While commentary on the limitations of Baron and Kenny's method and extensive discussion on mediation analysis are out of the scope of the current study, the key takeaway is that a significant direct effect of X on Y does not always imply mediation and an insignificant direct effect does not necessarily suggest the absence of mediation (Hayes, 2017; Memon et al., 2018; Shrout & Bolger, 2002; Zhao et al., 2010). Thus, with the strong theoretical support of the immigrant revitalization perspective and the significant influence of immigration on crime across different waves of data and samples, I proceed to conduct further mediation analyses to investigate the mechanism of immigration-crime nexus through the role of immigrant social capital.

Pre-mediation Analyses

In this section, I establish the relationships among immigrant prevalence, neighborhood crime, and immigrant social capital utilizing the NNCS3-P sample (N=11,115 tracts across 18 cities). These analyses provide an understanding of how immigration is associated with neighborhood crime (path *c* in Figure 2), how immigration influences immigrant social capital (path *a* in Figure 2), and how

immigrant social capital is related to neighborhood crime over the past two decades (path *b* in Figure 2).

I. The Association between Immigration and Neighborhood Crime

Table 3 reports the effect of immigration on violent crime and burglary. Using the panel data, I find that immigrant prevalence significantly reduces both violent crime and burglary. When holding socio-economic neighborhood characteristics constant, a one-unit increase in immigrant prevalence is associated with a 5% ($100 \times (e^{-0.05} - 1)$) decrease in violent crime rate and a 14% ($100 \times (e^{-0.146} - 1)$) decrease in burglary rate. This finding is consistent with prior literature on the immigrant revitalization perspective that immigration reduces crime. More importantly, different from the cross-sectional models, panel data analyses of violent crime and burglary demonstrated a statistically significant relationship between immigration and crime in that there is an established immigration-crime relationship to explore potential mediating influences of immigrant social capital.

II. The Association between Immigration and Social Capital

In Table 4, I investigate the influence of immigrant prevalence on each of the immigrant social capital indicators. As expected, Model 1 shows that immigration and stable family structure are positively associated, and this relationship is statistically significant. A one-unit increase in neighborhood immigrant prevalence is associated with a about 0.3 unit increase in the stable family index when holding all else constant. On the other hand, the significant inverse relationship between immigration and multigenerational families is unexpected. I will discuss these

findings in detail in the discussion section. In terms of the local economy, consistent with immigrant revitalization, Model 3 and Model 4 of Table 4 demonstrate that immigration significantly increases the prevalence of consumer-facing local businesses and self-employment in the neighborhoods. In sum, except for the multigenerational family, immigration is significantly associated with a higher level of social organizations that produce immigrant social capital as hypothesized.

III. The Association between Social Capital and Neighborhood Crime

In Table 5a and Table 5b, I present the relationship between immigrant social capital and violent crime and burglary separately. For violent crime (Table 5a), all mediators are significantly associated with crime across models. When controlling for other socio-economic factors, both stable family structures and multigenerational families significantly reduce neighborhood violence. Yet, consumer-facing local businesses and self-employment significantly increase violent crime at the neighborhood level. Findings for burglary models (Table 5b) resemble those of violent crime, except for multigenerational families. The prevalence of multigenerational families does not influence neighborhood burglary crime (Table 5b Model 2). These findings provide partial support to the hypothesis that social organizations that produce immigrant social capital are negatively and significantly correlated with neighborhood crime. Instead, some of them may increase neighborhood crime. A more detailed discussion will be provided in Chapter 5.

Mediation Analyses

I. Fixed Effect Panel Data Analyses

In Table 6a and Table 6b, I present how changes in immigrant prevalence influence the changes in neighborhood crime from 2000 to 2020 using multilevel fixed effect models. Presented as the baseline models, Model 1 in Table 6a is the violent crime model in Table 3, and Model 1 in Table 6b is the burglary model in Table 3. To reiterate, immigrant prevalence significantly reduces both violent crime and burglary longitudinally. Next, I include indicators of immigrant social capital one by one to explore whether they explain the immigration-crime relationship.

First, I introduce the stable family index into the regressions. For both neighborhood violence and burglary, including the stable family index in the models reveals noteworthy changes in the immigration-crime relationship. The influence of immigration on violent crime has changed from negative (in Table 6a Model 1) to positive (Table 6a Model 2) after considering stable family structure in that a one-unit increase in immigrant prevalence is associated with an average of about 3% ($100 \times (e^{0.033} - 1)$) increase in violent crime rate. Meanwhile, a stable family structure is significantly reducing violent crime. The changes in coefficient from negative to positive after controlling stable family structures indicate that the protective influence of immigration on violence has its source in stable family structures.

For burglary, although the relationship between immigration and burglary stays negative after considering for the stable family index, the coefficient has changed that a one-unit increase in immigrant prevalence is associated with an average of about 10% ($100 \times (e^{-0.110} - 1)$) decrease in burglary (Table 6b Model 2), which is a 4%

difference compared to Model 1 in Table 6b. The direction and effect of stable families on crime is as expected that stable family structure is significantly inverse related to neighborhood crime.

Second, Model 3 includes multigenerational families when predicting crime. While multigenerational families are significantly associated with less violent crime but have a null relationship with burglary, resembling the findings in Table 5, the multigenerational family is not found to be very influential in the immigration-crime relationship. Different from findings for the stable family structure, for violent crime, there is only a slight change in the coefficient of immigrant prevalence – a change from 0.033 to 0.030 when comparing Model 2 and Model 3 in Table 6a. For burglary, there is no change (See Model 2 and Model 3 in Table 6b).

Third, I investigate whether including customer-facing local businesses in the regressions will affect the immigration-crime relationship, as shown in Model 4. For violent crime (Table 6a Model 4), immigration still significantly increases crime as in Model 2 and Model 3 but the coefficient becomes smaller (from $\beta = 0.033$ to $\beta = 0.025$), meaning the protective effect of immigration on violent crime is slightly diminished by businesses. Similar to the violent crime model, the coefficient of immigrant prevalence changes from -0.11 to -0.12 for burglary (Model 3 and Model 4 in Table 6b) also indicates that the benefit of immigration on burglary is weakened by customer-facing local businesses. Meanwhile, the more customer-facing local businesses are associated with more violent crime and burglary in the neighborhood. This finding is more consistent with the literature that businesses are crime attractors/generators than immigrant revitalization perspective.

Lastly, Model 5 controls for self-employment, and all other mediators, when examining the influence of immigrant prevalence on crime. Comparable to customer-facing local businesses, a higher level of self-employment is associated with more violent crime and burglary. Compared with Model 4, the coefficient of immigrant prevalence of violent crime also decreases from 0.025 to 0.022 (and from -0.116 to -0.118 for burglary respectively).

To conclude, the fixed effect analyses show that stable family structures explained a large part of the immigration-crime relationship and that the signs of the relationships have changed from negative to positive after controlling for the stable family. While the immigration-crime association slightly changes after considering other immigrant social capital measures, the changes are too minor to determine their contribution to the immigrant revitalization process.

II. Temporally Ordered Mediation Analyses

Tables 7a-d and 8a-b examine the mediation effects of immigrant social capital in a temporally ordered manner, meaning specifying Immigration Prevalence at Wave 1, mediators at Wave 2, and neighborhood crime at Wave 3 (as indicated in Figure 4).

First, Table 7a presents the result of the mediation effect of stable family structures. The direct effect of immigrant prevalence on violent crime is positive and significant, while the effect for burglary is insignificant. Although consistent with the cross-sectional Wave 3 models in Table 2a and 2b, the positive relationship between immigration and neighborhood violence contrasts with most of the prior research, as well as findings in the previous analyses using panel data. Holding all else constant,

the level of immigrant prevalence in the neighborhood is associated with about 8% ($100 \times (e^{0.081} - 1)$) increase in violent crime rate.

More importantly, Table 7a shows that the stable family indicator has a statistically significant indirect effect on violent crime, but not burglary. Neighborhoods with a higher degree of immigrant prevalence are more likely to have a higher level of stable families, and in turn, neighborhoods with more stable families are more likely to have less crime. The significant mediating influence is also shown by the coefficient of immigrant prevalence on crime, which has changed from positively significant to null after considering the mediating influence of stable families. On the other hand, immigrant prevalence stays insignificant in predicting burglary after taking neighborhood stable family structures into account.

Table 7b indicates that the multigenerational family indicator does not have the expected mediating influence on the immigration-crime nexus. Immigrant prevalence has null effects on violent crime and burglary, and there are no significant indirect effects on multigenerational families. Surprisingly, a higher prevalence of multigenerational families is associated with more neighborhood violence, which is not in line with the immigrant revitalization perspective or social disorganization theory.

Tables 7c and 7d present the results on the direct relationship between immigration and crime, and the indirect effect of a neighborhood's local economy in this relationship. While neighborhoods with higher levels of immigrant prevalence do not have more consumer-facing local businesses as expected by the immigrant revitalization perspective, an increase in local businesses is significantly associated

with more violent crime and burglary at a later time. These models show that local businesses do not have a mediating influence on the immigration-crime relationship.

Findings for self-employment resemble those of customer-facing local businesses. Similarly, immigrants with a higher prevalence of immigration do not show the expected growth in self-employment, as proposed by immigrant revitalization theories. While a unit increase in self-employment is associated with a 0.01 unit increase in burglary (Table 7d) when all else is controlled, this positive and significant relationship between self-employment and crime is not found for violent crime. Again, the path analyses do not find a statistically significant indirect effect for self-employment, for both neighborhood violence and burglary.

The final step in my analysis is to determine the extent to which mediating measures of immigrant social capital (stable families, multigenerational families, business ownership, and self-employment) collectively explain the relationship between immigration prevalence on neighborhood crime. This is done by including each measure in the model one by one. Table 8a shows that stable family structure is the primary way in which immigration reduces violent crime. As shown in Model 1, the stable family index explained around 30% (-0.020 /0.061) of the total effect of immigration on violent crime, and the effect of immigrant prevalence on crime has changed from positive significant to null after accounting for stable family structures.

While multigenerational families, local businesses, and self-employment do not have any influence on the immigration-crime relationship, the total indirect effect becomes insignificant after considering the local economy measures that the indirect effect of stable families disappears. As evidenced by Models 2 and 3 in Table 8b, the

total effect of immigrant prevalence on violent crime has changed from non-significant to positive significant. However, burglary models demonstrate that the immigration-burglary relationship does not work through immigrant social capital (Table 8b), as expected following the immigrant revitalization perspective.

In sum, evident by both fixed-effect models and temporally ordered models, immigrant revitalization is realized by introducing more stable families in neighborhoods, thereby correlating immigration with a reduction in neighborhood violence.

Chapter 5: Discussion and Conclusion

Although researchers have conducted extensive investigations into the immigration-crime relationship at the neighborhood level (Ousey & Kubrin, 2018), only a handful of works have delved into *how* this relationship operates, especially the mechanisms by which immigration influences neighborhood crime, comprehensively and in a larger sample. In this dissertation, building on the immigrant revitalization perspective, I explore how immigration affects neighborhood crime through immigrant social capital. Immigrant social capital is the engine behind immigrant revitalization because immigrant communities bring about a social organization that helps to establish close-knit social networks, reinforce mutual norms and expectations, and allow exchanges of resources. Meanwhile, these forms of immigrant social capital also facilitate community social controls that result in safer environments in immigrant neighborhoods. Hence, in this dissertation, I strive to advance the field by mapping out the intervening mechanism between immigration and neighborhood crime and identifying immigrant social capital as stable families, multigenerational families, local businesses, and entrepreneurship.

This dissertation finds immigration produces a protective effect against neighborhood crime mostly by increasing stable family structures. This effect is particularly strong for violent crime. In the fixed effect model, the immigration-crime link changes from negative to positive AFTER controlling for a stable family structure. Similarly, in the GSEM model, I find that immigration has a null effect on violent crime because stable families neutralize the positive association between immigration and crime. However, the benefits of stable families for burglary depend

on model specifications. Consistent with violent crime, fixed effect models show that while communities with a higher share of immigrants are always associated with less burglary, these communities can enjoy greater crime reduction benefits because they have more stable families. Yet, the benefit of stable families is not found for burglary in the GSEM model. One possible explanation for different findings between violent crime and burglary in the GSEM model could be due to the distant time points between waves. As the waves in NNCS3-P are around ten years apart, the effect of immigrant prevalence in 2000 on burglary in 2020 needs to be extremely strong to be detected.

Immigration increases the presence of stable families and thereby protects communities against crime. A key way by which immigration revitalizes communities is through family formation. According to the literature on community and crime, close-knit social networks are an indicator of the private level of the systemic model. Private ties, which are fueled by family relationships and friendships, help to bring about private social controls such as parental supervision of children's behavior and prosocial friends keeping one away from delinquency. Especially for private social control, it is well acknowledged that "broken homes" – the lack of a strong private social network – weaken social controls and community collective efficacy and lead to delinquency due to weak attachment to the parent and poor child-rearing environments (Farrington, 2011; Morenoff et al., 2001). Although some research shows that, depending on the nature of the social networks, a close-knit social relationship may increase crime and victimization (Browning et al., 2004; Duck, 2015; Pattillo, 1998), the family-orientated nature of immigrant families

suggests that the pro-social private network is more likely to exert private social control that reduces crime than produces crime.

Because immigrant families are more likely to be married, form intact two-parent households, and not divorce, immigrant communities are more likely to have a higher presence of stable families (Lichter et al., 2015; Mayol-García et al., 2021; National Academies of Sciences & Population, 2016; Zill, 2016). The stability of immigrant families portrays familism, meaning putting family as the priority and valuing mutual support among family members. The closed-knit private social network in immigrant communities, due to the formation of stable families, promotes informal/private social control. Especially since immigrant social capital shares characteristics of a socially organized community, immigrant communities with more stable families are expected to have greater community social control that protects residents from crime (Bursik & Grasmick, 1993; Kao, 2004).

The analyses do not find any support for the intervening influence of multigenerational families and the local economy. The unexpected findings of multigenerational families specifically warrant additional discussion. First, neighborhoods that have more immigrants have fewer multigenerational families. Recall that I expected there to be more multigenerational families due to the family-oriented culture of most immigrants. An explanation for this unexpected finding may be related to the changes in socioeconomic status in the recent wave of immigration. Oftentimes, besides cultural preference, a multigenerational family is the product of structural obstacles (Fong & Berry, 2017). The adult children of immigrants may decide to stay with the family due to the high cost of housing. Working immigrant

parents may need grandparents to support childcare. For elderly immigrants facing language barriers and social isolation, their only choice may be to stay with their children. However, an increasing number of immigrants are coming from better socioeconomic backgrounds and have higher levels of education. There is a 5% increase in adult immigrants who have a bachelor's degree for the past twenty years (Budiman, 2020). Moreover, according to the 2018 ACS, compared to the native-born, immigrants are more likely to have a spouse who has a bachelor's or advanced degree (Olsen-Medina & Batalova, 2020). In this case, a neighborhood with more immigrants may have fewer multigenerational families because more recent immigrants have higher average socioeconomic status and thus less need to live with their extended family. In fact, in the NNCS3-P neighborhoods, despite stable trends of immigration across the three waves, multigenerational families have slightly decreased over the past 20 years (shown in Table 1).

Another explanation is immigrant assimilation and the rise of second-generation immigrants. Immigrants may assimilate with the host society and adopt the culture, characterized as acculturation. Immigrant assimilation is "the process through which minorities become incorporated into the mainstream culture" (pg. 39) and this process is inevitable as immigrants spend more time in the host society (Morenoff & Astor, 2006). Moreover, assimilation could also be spatial in that as immigrants accumulate wealth and move up the social ladder, they are more likely to reside in neighborhoods that have higher socioeconomic status and closer contact with members of the host society (Fong & Berry, 2017; Massey & Mullan, 1984). This

upward mobility, combined with the "Americanization" of their family values, might contribute to the lower prevalence of multigenerational families among immigrants.

Meanwhile, the rise of second-generation immigrants also shows better economic conditions for immigrant families. As of 2018, 12% of the U.S. population is second-generation immigrants, which has increased by about 2% since 2020, and Pew projects that it will reach about 20% by 2050 (Budiman et al., 2020; Pew Research Center, 2013). More importantly, these second-gen immigrants have higher median household income, education, homeownership rates, and lower poverty rates compared to first-gen immigrants (Pew Reseach Center, 2013). A recent book investigating income trajectories of people born between 1978 and 1983, immigrant children finds that children of immigrants are exceptionally better at moving up the economic ladder than the children of native-born (Abramitzky & Boustan, 2022; Coy, 2022). For instance, 15% of children of immigrants are rich by their mid-30s compared to 9% of the children of U.S.-born. Hence, economically, immigrant families may decrease their reliance on their extended families.

Unexpectedly, the GSEM analyses do not demonstrate a significant mediating influence of multigenerational families in the immigration-crime relationship. More importantly, the results show that a neighborhood with more multigenerational families at Wave 2 is associated with more violent crime at Wave 3. It may be the case that this observed association is attributable to the correlation between multigenerational families and structural disadvantages. When looking at the correlation matrix of all variables (Appendix C Table C1-3), the percentage of multigenerational families has a considerable positive association with the

neighborhood disadvantages index (β = 0.75 at wave 1, 0.64 at wave 2, and 0.55 at wave 3), which is almost the highest correlation in the entire correlation matrix.

Knowing that neighborhood disadvantage is one of the most resilient predictors of neighborhood crime, the presence of multigenerational families may represent a form of neighborhood disadvantage rather than an advantage. As discussed above, multigenerational households are often products of structural and economic disadvantages, and this still could be true even when the parents of the children are present in the multigenerational household. However, the multigenerational family measure in this study only captures the general presence of grandparents, meaning we do not know whether the parents are also living with and taking care of their children. In the case that the measure mostly captures households that have only the children and the grandparent with no parent present, the multigenerational family variable may become a measure of "skipped generation" families. Although limited studies investigate the formation of grandparent-grandchildren households, in general, a skipped-generation family is formed when parents are no longer able to take care of their children, due to reasons such as incarceration, physical/mental illness, substance abuse, or economic problems (Pebley & Rudkin, 1999). Moreover, in skipped-generation families, the grandparents generally have poorer physical and mental health, the grandfamilies are poorer economically, and the grandchildren have worse behavior problems and academic outcomes (Pilkauskas & Dunifon, 2016). In this situation, the presence of grandchildren-grandparent households is indicative of "broken homes" and neighborhood disadvantages.

Another explanation for this finding relates to the tensions within multigenerational families. Although these families could facilitate family support and boost informal social control (Foner & Dreby, 2011; A. Portes & Rumbaut, 2006), some literature also finds that living with extended family members is associated with higher risks of familial conflict, especially for children of immigrants (Kang & Cohen, 2017). While beneficiaries of the emotional and instrumental support from their grandparents, children and young adults in the family could also experience tensions between their grandparents and parents, as well as between themselves and their parents (Pittman et al., 2016). In both individual and neighborhood-level studies, these parental conflicts and family disruptions significantly predict individual offending and neighborhood crime and victimization (Bursik, 1999; Bursik & Grasmick, 1993; Farrington & Loeber, 1999; Sampson, 1986; Stritzel et al., 2021). In addition, based on routine activities theory, there is limited empirical evidence on whether grandparents are physically capable of supervising neighborhood activities. The prevalence of multigenerational families in a community may indicate vulnerability rather than capable guardianship in a community.

In this case, the presence of multigenerational families, with disadvantages and endemic conflicts, may represent a form of neighborhood disadvantage rather than an advantage. The negative sides of multigenerational families may explain the positive relationship between multigenerational families and neighborhood crime. Moreover, the benefits and drawbacks of multigenerational families on crime may offset each other and wash away its influence.

Another finding that contradicts the immigrant revitalization perspective is that the local economy, defined as the prevalence of local businesses and entrepreneurship, does not have any mediating influence on the immigration-neighborhood crime relationship. I find places with higher levels of immigrant prevalence have more local businesses and self-employment, but these communities are also associated with more violent crime and burglary. This finding, however, adheres to the literature on the criminogenic effect of business facilities following environmental criminology and routine activity theory. The level of immigrant prevalence in a neighborhood has no significant influence on the performance of the local economy.

Given the existing literature, the absence of the mediation effect of local businesses and entrepreneurship is also unexpected. Unlike Stansfield's (2014) study at the city level, I found immigrant prevalence has a null effect on self-employment in the GSEM model, and an explanation for this disparity can be due to differences in measurement. While Stansfield (2014) utilized the number of Hispanic-owned firms in the city as an indicator of ethnic entrepreneurship, the measure used in this study (self-employed) is not race- or ethnicity-specific. However, this is also a limitation for my other measures of immigrant social capital in this study, as well as in some other studies, that the operationalization of immigrant social capital is not specific to immigrants or racial/ethnic groups.

I also find that the number of local businesses in a neighborhood is positively related to both violent crime and burglary. Although contradictory to the immigrant revitalization perspective, my findings are more consistent with one neighborhood-

level study. When looking at neighborhoods in Southern California, Kubrin and her colleagues (2019) found that, against their expectation, neighborhoods with more immigrant/ethnic-run local businesses have higher levels of violent and property crime. Besides limitations due to possible measurement errors and how one defines and measures 'neighborhood', the current findings encourage future efforts of theory revision.

In sum, immigration may reduce neighborhood crime, but the story is *less* about the local economy and *more* about family structure, which is the source of private social control, neighborhood guardianship, and other unobserved mechanisms like collective efficacy. My findings partially support the immigrant revitalization perspective wherein immigration reduces neighborhood crime only through stable family structures, but neither through multigenerational families nor the local economy. Nonetheless, this multifaceted examination of the immigration-crime nexus, cross-sectionally and longitudinally, supports previous literature that finds that immigration generally has a null effect on crime (Ousey & Kubrin, 2018). In line with Ousey and Kubrin (2018), when immigration has a significant relationship with crime, it is usually negative – meaning a higher level of immigrant prevalence is associated with less crime in a neighborhood.

The limitations and findings of this dissertation suggest avenues for future research. First, the findings from neighborhoods in the 18 cities in the NNCS3-P may only speak to neighborhoods with an established immigrant history and population. Most cities (15 out of 18) in the NNCS3-P are gateway cities – places that have a long history of immigrant settlement (Singer, 2004, 2012). As discussed earlier,

studies have shown that city context matters in understanding the immigration-crime relationship (Harris & Feldmeyer, 2013; Lyons et al., 2012; Painter-Davis, 2016; Ramey, 2013; Vélez & Lyons, 2012). It may be the intervening benefits of stable families in the immigration-crime link at the neighborhood level are only viable because of the receptive and protective context of the cities (e.g., external investments or sanctuary policy).

Moreover, there is a possibility of sample selection bias for the NNCS3-P sample as the 18 cities are also places that are more liberal, urban, and possess the resources to build open data portals, which might weaken the generalizability of the result observed in analyses. As noted in the data collection procedure of NNCS3-P, the 18 cities were selected due to the availability and reliability of crime data through their cities' or police departments' open data portal. With the increasing need for government transparency and accountability globally and in the United States, more cities are building open data portals and sharing information ranging from demographic, housing, economic, and public safety. However, building data portals and sharing a large amount of administrative data is resource-intensive. While the original NNCS2-P consists of large to medium cities in the U.S., the cities in NNCS3-P are only some of the largest cities in the U.S., such as Los Angeles, Chicago, Dallas, and Austin. These big cities are more likely to have the resources to make data available and thus be included in the sample. Hence, future research should look to (1) complete the collection of NNCS3-P with a wider and larger representative sample of neighborhoods and (2) consider city context when investigating the immigration-crime mechanism.

Besides the city context, it is also important to consider the non-urban context of the immigrant-crime link. While NNCS neighborhoods tell us about the immigration-crime relationships in urban neighborhoods, considered to be ethnic enclaves, there are increasing immigrant communities that are developing in suburban areas – so-called "ethnoburbs." For instance, the number of Asian American ethnoburbs increased thirty-fold from 1980 to 2010 (Kye, 2018). These ethnoburbs are generally ethnoburbs are better off compared to the traditionally poor transitory ethnic enclaves. Kye (2018) shows that ethnoburbs, although mostly racially and ethnically homogenous, have fewer foreign-born residents and lower levels of poverty than urban enclaves. In this case, the growing number of suburban immigrant neighborhoods indicates the rise of second-generation immigrants. However, we know little about how second-generation immigrants shape social networks, social capital, socioeconomic conditions, and their relations to crime in ethnoburbs, as they move up the economic ladder and can mobilize more resources. While urban immigrant communities may protect neighborhoods from crime by producing immigrant social capital, the socioeconomic advantages in ethnoburb may strengthen such benefits and warrant further investigation.

Second, the current measure of immigration and immigrant social capital in this study ignores the racial/ethnic makeup of the immigrant population. The premise of immigrant revitalization is that immigrant communities are homogenous even though the immigrant population is very diverse. Thus, communities full of immigrants from the same racial-ethnic groups who share the same background and culture are more likely to stabilize neighborhoods, enable social control, and reduce

crime. When examining the immigration-crime relationship in Southern California, Kubrin and colleagues (2018) graphically illustrated that immigrant neighborhoods are homogenous in that people from the same race/ethnic group or the same region (in the world) of the country of origin are spatially concentrated in the same neighborhood. They also found that distinguishing immigrant groups better predicts crime at the neighborhood level than using general measures of immigration, such as percent foreign-born. Future research should capture the heterogeneity in the immigrant population and homogeneity within the immigrant communities when measuring both immigration and immigrant social capital.

Third, measures of structural conditions of a neighborhood do not necessarily accurately capture immigrant social capital. Immigrant social capital is the way in which immigration reduces neighborhoods because the sources of immigrant social capital – obligations and expectations, informal channels, and social norms – are also the ingredients for a community to exert social control and prevent crime. However, none of these elements are actually measured in the current study. Future research should consider conducting surveys for residents of a representative sample of neighborhoods and asking behavioral and perspective questions to tap into the different dimensions of social capital and community social control.

Fourth, measures of crime using official crime data may underestimate the level of crime in a neighborhood due to the reluctance of immigrants to seek help from law officials. While there is limited research on immigration and crime reporting, the current literature suggests that crime in immigrant communities could be less likely or more likely to be reported to law enforcement (see Xie & Baumer

(2019)) for a detailed discussion on theories of immigrant victimization and reporting). Crime in immigrant communities may be underreported due to unpleasant experiences with legal authorities that lead to higher levels of legal cynicism – distrust of law enforcement due to the perception of an unfair and unjust legal system. For example, immigrants, or their immediate families, who are undocumented may have direct and indirect negative interactions with law officials that further avoid and distrust the criminal justice system. In addition, with undocumented immigrants being heavily dependent on an underground cash-only economy, they are less likely to report crime to the officials due to their illegal status and activities albeit a higher chance of being victimized (Barranco & Shihadeh, 2015; Xie & Baumer, 2021). Especially with the spike in hate crimes against immigrants during the COVID-19 pandemic that part of the NNCS3-P study period covers, it is possible that official crime data do not provide a full picture of crime problems in immigrant communities.

However, per the immigrant revitalization perspective, residents in immigrant neighborhoods are more likely to report crime due to closer social ties and trust that build social organization and social control (Martinez, 2002; Ousey & Kubrin, 2009; Vélez, 2001). In fact, in immigrant counties that are traditional immigrant destinations, the level of violent crime reporting resembles that of non-traditional immigrant counties (Xie & Baumer, 2019). As the majority of the neighborhoods in NNCS3-P are traditional immigrant destinations, concern that official crime data is underestimated is less detrimental to the validity of the findings.

Fifth, while there are three main ways in which immigration revitalizes communities, this dissertation is unable to examine the role of border local

institutions in the communities (e.g., immigrant-serving non-profit organizations or churches). As described in Chapter 2, immigration utilizes local institutions to assist with settlement and assimilation, as well as to improve neighborhood well-being by strengthening those local institutions (Vélez, 2009). Although a study at the neighborhood level found that the presence of ethnic/immigrant voluntary organizations has no relationship with crime (Kubrin et al., 2019), Ramos et al. (2023) found that ethnic/immigrant organizations at the city level are the only significant mediating influence between immigration and violent crime. Considering the mixed findings from the limited studies available, I suggest future endeavors when investigating the role of local institutions should consider spatial proximity to local institutions. Compared to families or businesses, local institutions are more sparsely located across a city. However, it is hard to imagine that an institution like immigrant non-profits or churches will only serve immigrants in the neighborhood they are physically located. Thus, further investigation of local institutions for immigrants is needed to provide a more comprehensive picture of the immigration-crime relationship.

Lastly, despite the causal nature of the research questions, the employed modeling strategies have limited implications for making a causal conclusion about the immigration-crime relationship. While longitudinal data help to account for time-varying cofounders, I cannot establish the temporal order of immigration, social capital, and crime. While the GSEM model forced the temporal order of the immigration-crime relationship, this modeling strategy assumes immigration "happens" before social capital and crime. This assumption ignores the possibility

that the previous level of crime may affect immigration, thus affecting immigration social capital, then crime – meaning immigrants may be more likely to move to places that have less crime. Acknowledging the difficulties in identifying cause-outcome in social science and the immigration-crime relationship is dynamic, future studies should try to capture the potential recursive relationship between immigration and neighborhood crime using other analytical strategies, such as cross-lagged models.

There is no doubt that the U.S. is a nation of immigrants. As the share of immigrants reaches a historic high, immigrants and their descendants are projected to account for 37% of the U.S. population by 2050 (Pew Research Center, 2013). Nonetheless, public sentiments connecting immigrants and crime are everlasting. Knowing that there will be an increasing prevalence of immigrants in our communities, as well as immigrant neighborhoods in urban and suburban areas, it is important to understand the underlying mechanism between immigration and crime to mitigate preconceptions about immigrants and alleviate interracial conflicts. Especially with the rise of second-generation immigrants, it is critical to consider the role of assimilation as a neighborhood process that may cultivate or thwart the development of immigrant social capital and revitalization.

Despite its limitations, this dissertation contributes to the current literature by empirically testing the immigration revitalization perspective in a large sample of neighborhoods across the U.S. The findings highlight the importance of stable family structures in explaining the protective influence of immigration on crime. The results also invite researchers to investigate further the roles of multigenerational families

and the local economy in the immigrant revitalization process. Moreover, future studies should emphasize further data collection, measurement of key concepts, city contexts, and local institutions. In light of the current literature, I hope this dissertation convinces the readers that there is no empirical evidence of "crimmigration," but rather "revimmigration."

Table 1. Descriptive Statistics for Neighborhood Crime and Structural Characteristics of NNCS3-P (N = 3,705 census tracts across 18 cities)

	Wave 1 (1999-2001)				Wave 2 (2010 - 2013)				Wave 3 (2017 - 2021)			
	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
Dependent Variables												
Average Violent crime count (Homicide & Robbery)	17.27	17.75	0.00	204.00	12.08	12.99	0.00	148.00	6.51	9.95	0.00	119.00
Average Burglary crime count	37.34	27.86	0.00	311.00	31.43	26.17	0.00	215.00	18.14	19.20	0.00	281.00
Independent Variable												
Immigrant prevalence												
% Foreign-born	22.45	18.29	0.00	79.11	22.59	17.15	0.00	78.26	21.87	15.28	0.00	75.68
% New immigrants	10.17	9.43	0.00	57.30	7.73	7.31	0.00	43.75	10.24	8.29	0.00	55.02
% Linguistic isolation	10.84	12.40	0.00	72.99	10.96	12.50	0.00	80.00	8.80	9.93	0.00	65.05
Mediators												
Stable family												
% Married-couple family	38.45	15.53	0.00	90.55	34.52	15.31	0.00	89.88	34.72	15.57	0.00	88.30
% Children living in married-couple family	63.98	20.94	0.00	100.00	56.57	24.39	0.00	100.00	59.00	24.59	0.00	100.00
% Multigenerational family	5.25	4.28	0.00	27.82	4.39	4.18	0.00	39.82	3.53	3.70	0.00	32.55
Local customer facing business rate per 1000	1.49	2.74	0.00	58.51	3.80	5.47	0.00	85.52	6.27	8.46	0.00	152.50
% Self-employed	8.82	5.89	0.00	46.76	9.88	6.89	0.00	76.54	10.33	6.65	0.00	47.31
Control Variables												
Disadvantage	0.10	0.90	-1.60	3.68	0.04	0.86	-1.59	3.17	0.21	0.89	-1.42	3.41
% Joblessness	34.71	13.11	5.01	78.98	33.74	12.06	6.01	79.96	28.77	11.03	3.83	76.28
% Professional workers	33.09	17.72	0.00	80.00	35.91	19.48	0.00	91.94	42.60	20.38	0.00	88.40
% Highschool graduates	72.59	19.41	14.12	100.00	79.48	16.48	25.25	100.00	84.25	13.77	30.91	100.00

Table 1. Descriptive Statistics for Neighborhood Crime and Structural Characteristics of NNCS3-P (N = 3,705 census tracts across 18 cities)

	Wave 1 (1999-2001)				Wave 2 (2010 - 2013)				Wave 3 (2017 - 2021)			
	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
% Female-headed households	16.85	11.87	0.00	80.41	17.40	12.31	0.00	70.82	15.16	11.11	0.00	85.94
% Secondary sector workers	18.27	8.69	0.00	68.82	22.03	11.12	0.00	66.22	20.98	11.11	0.38	71.86
% Population lives under poverty line	19.26	13.44	0.00	79.71	22.33	14.57	0.00	87.49	17.40	12.35	0.00	78.85
Residential instability	0.12	0.85	-1.93	2.64	0.11	0.86	-1.83	3.75	0.42	0.83	-1.39	4.48
% Renter occupied housing units	55.42	24.59	0.00	100.00	55.60	23.84	0.00	100.00	55.91	23.66	0.56	100.00
% Recent movers 5 years older	51.73	13.72	13.20	99.03	18.51	10.32	0.00	74.91	15.20	9.66	0.00	73.89
Foreclosure Rate per 1,000	4.26	6.21	0.00	74.83	12.02	18.96	0.00	957.00	9.96	11.73	0.92	581.80
% Young male (15-34)	16.97	5.99	2.38	50.22	16.63	6.24	0.00	51.53	16.03	6.38	1.32	51.45
% Vacant housing	6.75	5.56	0.00	40.94	10.75	8.17	0.00	71.08	9.25	7.00	0.00	57.50
White Neighborhood	0.30	0.46	0.00	1.00	0.24	0.43	0.00	1.00	0.20	0.40	0.00	1.00
African American Neighborhood	0.14	0.35	0.00	1.00	0.13	0.34	0.00	1.00	0.11	0.31	0.00	1.00
Hispanic Neighborhood	0.11	0.31	0.00	1.00	0.13	0.34	0.00	1.00	0.13	0.33	0.00	1.00
Minority Neighborhood	0.09	0.29	0.00	1.00	0.10	0.31	0.00	1.00	0.11	0.31	0.00	1.00
Multi-ethnic Neighborhood	0.36	0.48	0.00	1.00	0.39	0.49	0.00	1.00	0.46	0.50	0.00	1.00
Violent crime spatial weights	5.30	4.36	0.00	48.89	3.75	3.29	0.00	29.62	34.31	41.73	0.00	453.00
Burglary spatial weights	11.16	6.64	0.77	70.76	9.15	5.95	0.10	36.14	94.82	77.06	0.00	839.20

Table 2a. Cross-sectional Poisson Models for Crime with Tract Population as Exposure - NNCS3 Panel Sample

	Violent Crime									Burglary								
Variables	Wave 1 (1999-2001)			Wave 2 (2010-2013)			Wave 3 (2017-2021)			Wave 1 (1999-2001)			Wave 2 (2010-2013)			Wave 3 (2017-2021)		
	b		SE	*b*		SE	*b*		SE	*b*		SE	*b*		SE	*b*		SE
Immigrant prevalence	-0.024		0.031	-0.055		0.037	0.058	*	0.025	-0.121	**	0.021	-0.165	**	0.030	-0.117	**	0.026
Disadvantage	0.162	**	0.046	0.199	**	0.043	0.155	*	0.077	0.121	*	0.056	0.164	**	0.043	0.017		0.043
Residential instability	0.254	**	0.034	0.261	**	0.024	0.201	**	0.021	0.036		0.022	0.028	*	0.011	0.114	**	0.036
Foreclosure Rate	0.009	*	0.004	0.003	**	0.001	0.024	**	0.003	0.007		0.004	0.002	*	0.001	0.015	**	0.002
% Young male (15-34)	0.005		0.006	0.008		0.005	0.004		0.005	0.011	**	0.003	0.004		0.003	-0.004		0.003
% Vacant housing	0.028	**	0.009	0.015	**	0.005	0.024	**	0.005	0.022	**	0.004	0.010	**	0.001	0.027	**	0.002
African American Neighborhood	0.807	**	0.163	0.905	**	0.172	0.679	**	0.145	0.155	*	0.065	0.378	**	0.092	0.263	*	0.131
Hispanic Neighborhood	0.359		0.192	0.456	**	0.087	0.205	**	0.058	-0.038		0.120	0.063		0.091	-0.111		0.113
Minority Neighborhood	0.581	**	0.139	0.728	**	0.087	0.543	**	0.108	0.119		0.072	0.357	**	0.063	0.184		0.108
Multi-ethnic Neighborhood	0.472	**	0.113	0.410	**	0.106	0.109		0.068	0.161	**	0.038	0.218	**	0.040	0.091		0.052
Spatial weights of crime	0.038	**	0.006	0.052	**	0.013	0.006	**	0.000	0.020	**	0.006	0.031	**	0.006	0.003	**	0.001
Constant	-7.153	**	0.168	-7.489	**	0.112	-7.646	**	0.145	-5.189	**	0.115	-5.252	**	0.077	-6.028	**	0.083

N = 3,705 tracts within 18 cities; ** p<0.01, * p<0.05

City dummies are included in the regressions but not shown on the table.

Table 2b. Cross-sectional Poisson Models for Crime with Tract Population as Exposure - NNCS2 Sample

	Violent Crime									Burglary								
Variables	Wave 1 (1999-2001)			Wave 2 (2010-2013)			Wave 3 (2017-2021)			Wave 1 (1999-2001)			Wave 2 (2010-2013)			Wave 3 (2017-2021)		
	b		SE	*b*		SE	*b*		SE	*b*		SE	*b*		SE	*b*		SE
Immigrant prevalence	-0.054	*	0.026	-0.038		0.029	0.058	*	0.025	-0.124	**	0.015	-0.146	**	0.020	-0.117	**	0.026
Disadvantage	0.276	**	0.045	0.279	**	0.028	0.155	*	0.077	0.203	**	0.036	0.217	**	0.027	0.017		0.043
Residential instability	0.214	**	0.020	0.276	**	0.014	0.201	**	0.021	0.044	*	0.019	0.062	**	0.012	0.114	**	0.036
Foreclosure Rate	0.001		0.001	0.002	*	0.001	0.024	**	0.003	0.001	**	0.000	0.002	**	0.001	0.015	**	0.002
% Young male (15-34)	0.007		0.004	0.001		0.004	0.004		0.005	0.010	**	0.003	0.001		0.002	-0.004		0.003
% Vacant housing	0.028	**	0.006	0.015	**	0.003	0.024	**	0.005	0.023	**	0.003	0.012	**	0.002	0.027	**	0.002
African American Neighborhood	0.583	**	0.135	0.629	**	0.113	0.679	**	0.145	0.077		0.048	0.224	**	0.055	0.263	*	0.131
Hispanic Neighborhood	0.314	*	0.134	0.294	**	0.049	0.205	**	0.058	-0.030		0.076	0.011		0.050	-0.111		0.113
Minority Neighborhood	0.513	**	0.094	0.522	**	0.058	0.543	**	0.108	0.110	*	0.049	0.227	**	0.047	0.184		0.108
Multi-ethnic Neighborhood	0.440	**	0.064	0.351	**	0.053	0.109		0.068	0.164	**	0.028	0.189	**	0.026	0.091		0.052
Spatial weights of crime	0.038	**	0.005	0.052	**	0.007	0.006	**	0.000	0.017	**	0.003	0.025	**	0.004	0.003	**	0.001
Constant	-6.682	**	0.078	-6.700	**	0.081	-7.646	**	0.145	-5.137	**	0.072	-5.052	**	0.089	-6.028	**	0.083
Number of tracts	7, 875			8,242			3,705			8,242			8,242			3,705		
Number of cities	75			76			18			76			76			18		

** p<0.01, * p<0.05

City dummies are included in the regressions but not shown on the table.

Wave 1 Violent Crime and Burglary sample size differs due to missing data on homicide and robbery

Table 3. Panel Multi-level Poisson Regression with City Random Effect and Tract Population as Exposure

Variables	Violent Crime			Burglary		
	b		SE	*b*		SE
Immigrant prevalence	-0.050	**	0.004	-0.146	**	0.003
Disadvantage	0.231	**	0.006	0.138	**	0.004
Residential instability	0.233	**	0.005	0.047	**	0.003
Foreclosure Rate	0.003	**	0.000	0.003	**	0.000
% Young male (15-34)	0.006	**	0.001	0.005	**	0.000
% Vacant housing	0.025	**	0.000	0.021	**	0.000
African American Neighborhood	0.820	**	0.015	0.287	**	0.009
Hispanic Neighborhood	0.391	**	0.017	-0.011		0.011
Minority Neighborhood	0.632	**	0.015	0.214	**	0.009
Multi-ethnic Neighborhood	0.393	**	0.011	0.173	**	0.006
Spatial weights of crime	0.009	**	0.000	0.003	**	0.000
Wave 2 (2010-2013)	-0.480	**	0.007	-0.296	**	0.004
Wave 3 (2017-2021)	-1.656	**	0.010	-1.303	**	0.006
City-level random intercept variance	0.000		0.003	0.000		0.002
Constant	-6.817	**	0.024	-4.832	**	0.012

N = 11,115 tracts within 18 cities for three waves (3,705 tracts per wave); ** p<0.01, * p<0.05.
City and Wave dummies are included in regressions but not shown in the table.

Table 4. Panel Multi-level Poisson Regression with City Random Effect of Immigrant Prevalence and Mediators

Variables	Model 1: Stable family			Model 2: Multigenerational family			Model 3: Consumer-facing local business			Model 4: Self-employment		
	b		SE	*b*		SE	*b*		SE	*b*		SE
Immigrant prevalence	0.270	**	0.037	-0.385	**	0.106	0.253	**	0.08	0.521	**	0.177
Disadvantage	-0.423	**	0.027	2.493	**	0.151	-1.465	**	0.105	-2.093	**	0.221
Residential instability	-0.495	**	0.017	-1.236	**	0.146	0.993	**	0.083	-0.574	*	0.236
Foreclosure Rate	0.003	*	0.001	0.005		0.012	0.009	*	0.004	-0.014		0.011
% Young male (15-34)	-0.003		0.002	0.041	**	0.012	0.005		0.011	-0.205	**	0.020
% Vacant housing	-0.004	*	0.002	-0.007		0.006	0.113	**	0.009	0.130	**	0.034
African American Neighborhood	-0.723	**	0.080	2.073	**	0.295	0.989	**	0.267	-3.888	**	1.070
Hispanic Neighborhood	0.022		0.036	3.005	**	0.278	0.406		0.267	-4.306	**	1.485
Minority Neighborhood	-0.319	**	0.068	1.956	**	0.137	0.474		0.25	-4.409	**	1.480
Multi-ethnic Neighborhood	-0.201	**	0.059	1.117	**	0.108	0.113		0.148	-2.767	*	1.154
Wave 2 (2010-2013)	0.016		0.054	-0.872	**	0.170	1.726	**	0.125	0.690		0.429
Wave 3 (2017-2021)	0.326	**	0.065	-1.839	**	0.294	4.391	**	0.128	1.932	**	0.596
City-level random intercept variance	0.000	**	0.000	0.000	**	0.000	0.000	**	0.000	0.000	**	0.000
Constant	0.381	**	0.054	3.690	**	0.208	0.016		0.323	14.699	**	0.829

N = 11,115 tracts within 18 cities for three waves (3,705 tracts per wave); ** p<0.01, * p<0.05.

City and Wave dummies are included in regressions but not shown in the table.

Table 5a. Panel Multi-level Poisson Models of Mediators and Violent Crime with Tract Population as Exposure

Variables	Model 1			Model 2			Model 3			Model 4		
	b		SE	*b*		SE	*b*		SE	*b*		SE
Mediators												
Stable family	-0.260	**	0.006									
Multigenerational family				-0.008	**	0.001						
Consumer-facing local business (per capita)							0.030	**	0.000			
% Self-employed										0.008	**	0.001
Tract-level Covariates												
Disadvantage	0.145	**	0.006	0.234	**	0.006	0.275	**	0.006	0.226	**	0.006
Residential instability	0.113	**	0.005	0.209	**	0.005	0.196	**	0.005	0.224	**	0.005
Foreclosure Rate	0.004	**	0.000	0.003	**	0.000	0.003	**	0.000	0.003	**	0.000
% Young male (15-34)	0.008	**	0.001	0.006	**	0.001	0.004	**	0.001	0.007	**	0.001
% Vacant housing	0.024	**	0.000	0.026	**	0.000	0.023	**	0.000	0.026	**	0.000
African American Neighborhood	0.615	**	0.016	0.876	**	0.015	0.812	**	0.015	0.893	**	0.015
Hispanic Neighborhood	0.421	**	0.016	0.348	**	0.016	0.282	**	0.016	0.363	**	0.016
Minority Neighborhood	0.565	**	0.015	0.629	**	0.015	0.574	**	0.015	0.649	**	0.015
Multi-ethnic Neighborhood	0.349	**	0.011	0.376	**	0.011	0.328	**	0.011	0.388	**	0.011
Spatial weights of crime	0.008	**	0.000	0.009	**	0.000	0.008	**	0.000	0.009	**	0.000
Wave 2 (2010-2013)	-0.476	**	0.007	-0.488	**	0.007	-0.533	**	0.007	-0.487	**	0.007
Wave 3 (2017-2021)	-1.576	**	0.010	-1.652	**	0.010	-1.763	**	0.010	-1.649	**	0.010
City-level random intercept variance	0.000		0.003	0.000		0.003	0.000		0.003	0.000		0.003
Constant	-6.783	**	0.024	-6.767	**	0.025	-6.721	**	0.024	-6.910	**	0.026

N = 11,115 tracts within 18 cities for three waves (3,705 tracts per wave); ** p<0.01, * p<0.05.
City and Wave dummies are included in regressions but not shown in the table.

Table 5b. Panel Multi-level Poisson Models of Mediators and Burglary with Tract Population as Exposure

Variables	Model 1			Model 2			Model 3			Model 4		
	b		SE	*b*		SE	*b*		SE	*b*		SE
Mediators												
Stable family	-0.165	**	0.004									
Multigenerational family				0.001		0.001						
Consumer-facing local business (per capita)							0.017	**	0.000			
% Self-employed										0.008	**	0.000
Tract-level Covariates												
Disadvantage	0.038	**	0.004	0.083	**	0.004	0.110	**	0.004	0.098	**	0.004
Residential instability	-0.053	**	0.004	0.021	**	0.003	0.002		0.003	0.022	**	0.003
Foreclosure Rate	0.003	**	0.000	0.003	**	0.000	0.003	**	0.000	0.003	**	0.000
% Young male (15-34)	0.004	**	0.000	0.004	**	0.000	0.005	**	0.000	0.005	**	0.000
% Vacant housing	0.022	**	0.000	0.023	**	0.000	0.021	**	0.000	0.023	**	0.000
African American Neighborhood	0.239	**	0.010	0.392	**	0.009	0.382	**	0.009	0.424	**	0.009
Hispanic Neighborhood	-0.110	**	0.010	-0.166	**	0.010	-0.185	**	0.010	-0.139	**	0.010
Minority Neighborhood	0.134	**	0.009	0.166	**	0.009	0.158	**	0.009	0.197	**	0.009
Multi-ethnic Neighborhood	0.100	**	0.006	0.118	**	0.006	0.109	**	0.006	0.136	**	0.006
Spatial weights of crime	0.003	**	0.000	0.003	**	0.000	0.003	**	0.000	0.003	**	0.000
Wave 2 (2010-2013)	-0.291	**	0.004	-0.299	**	0.004	-0.328	**	0.004	-0.305	**	0.004
Wave 3 (2017-2021)	-1.208	**	0.006	-1.238	**	0.006	-1.275	**	0.006	-1.255	**	0.006
City-level random intercept variance	0.000		0.002	0.000		0.002	0.000		0.000	0.281	**	0.047
Constant	-4.763	**	0.012	-4.806	**	0.012	-4.803	**	0.012	-5.000	**	0.067

N = 11,115 tracts within 18 cities for three waves (3,705 tracts per wave); ** p<0.01, * p<0.05.
City and Wave dummies are included in regressions but not shown in the table.

Table 6a. Panel Multi-level Poisson Regression for Violent Crime with City Random Effect and Tract Population as Exposure

Variables	Model 1			Model 2			Model 3			Model 4			Model 5		
	b		SE	*b*		SE	*b*		SE	*b*		SE	*b*		SE
Immigrant prevalence	-0.050	**	0.004	0.033	**	0.005	0.030	**	0.005	0.025	**	0.005	0.022	**	0.005
Disadvantage	0.231	**	0.006	0.130	**	0.006	0.143	**	0.007	0.200	**	0.007	0.209	**	0.007
Residential instability	0.233	**	0.005	0.099	**	0.006	0.093	**	0.006	0.066	**	0.006	0.070	**	0.006
Foreclosure Rate	0.003	**	0.000	0.004	**	0.000	0.004	**	0.000	0.004	**	0.000	0.004	**	0.000
% Young male (15-34)	0.006	**	0.001	0.007	**	0.001	0.008	**	0.001	0.006	**	0.001	0.007	**	0.001
% Vacant housing	0.025	**	0.000	0.024	**	0.000	0.024	**	0.000	0.020	**	0.000	0.020	**	0.000
African American Neighborhood	0.820	**	0.015	0.623	**	0.016	0.634	**	0.016	0.574	**	0.016	0.602	**	0.016
Hispanic Neighborhood	0.391	**	0.017	0.388	**	0.017	0.399	**	0.017	0.359	**	0.017	0.387	**	0.017
Minority Neighborhood	0.632	**	0.015	0.550	**	0.015	0.559	**	0.015	0.518	**	0.015	0.548	**	0.016
Multi-ethnic Neighborhood	0.393	**	0.011	0.332	**	0.011	0.338	**	0.011	0.300	**	0.011	0.318	**	0.011
Spatial weights of crime	0.009	**	0.000	0.008	**	0.000	0.008	**	0.000	0.007	**	0.000	0.007	**	0.000
Wave 2 (2010-2013)	-0.480	**	0.007	-0.476	**	0.007	-0.480	**	0.007	-0.535	**	0.007	-0.540	**	0.007
Wave 3 (2017-2021)	-1.656	**	0.010	-1.560	**	0.010	-1.571	**	0.010	-1.700	**	0.010	-1.710	**	0.010
Mediators															
Stable family				-0.277	**	0.006	-0.274	**	0.006	-0.285	**	0.006	-0.284	**	0.006
Multigenerational family							-0.004	**	0.001	-0.003	**	0.001	-0.003	**	0.001
Consumer-facing local business (per capita)										0.031	**	0.000	0.030	**	0.000
% Self-employed													0.007	**	0.001
City-level random intercept variance	0.000		0.003	0.000		0.003	0.000		0.003	0.000		0.003	0.000		0.003
Constant	-6.817	**	0.024	-6.769	**	0.024	-6.753	**	0.025	-6.682	**	0.025	-6.783	**	0.027

N = 11,115 tracts within 18 cities for three waves (3,705 tracts per wave); ** p<0.01, * p<0.05.

City and Wave dummies are included in regressions but not shown in the table.

Table 6b. Panel Multi-level Poisson Models for Burglary with Tract Population as Exposure

Variables	Model 1			Model 2			Model 3			Model 4			Model 5		
	b		SE	*b*		SE	*b*		SE	*b*		SE	*b*		SE
Immigrant prevalence	-0.146	**	0.003	-0.110	**	0.003	-0.110	**	0.003	-0.116	**	0.003	-0.118	**	0.003
Disadvantage	0.138	**	0.004	0.092	**	0.004	0.093	**	0.005	0.122	**	0.005	0.134	**	0.005
Residential instability	0.047	**	0.003	-0.009	*	0.004	-0.010	*	0.004	-0.020	**	0.004	-0.015	**	0.004
Foreclosure Rate	0.003	**	0.000	0.003	**	0.000	0.003	**	0.000	0.003	**	0.000	0.003	**	0.000
% Young male (15-34)	0.005	**	0.000	0.005	**	0.000	0.005	**	0.000	0.006	**	0.000	0.007	**	0.000
% Vacant housing	0.021	**	0.000	0.020	**	0.000	0.020	**	0.000	0.018	**	0.000	0.017	**	0.000
African American Neighborhood	0.287	**	0.009	0.207	**	0.010	0.208	**	0.010	0.200	**	0.010	0.228	**	0.010
Hispanic Neighborhood	-0.011		0.011	-0.012		0.011	-0.011		0.011	-0.031	**	0.011	-0.002		0.011
Minority Neighborhood	0.214	**	0.009	0.179	**	0.009	0.179	**	0.009	0.172	**	0.009	0.203	**	0.010
Multi-ethnic Neighborhood	0.173	**	0.006	0.146	**	0.006	0.147	**	0.006	0.140	**	0.006	0.159	**	0.006
Spatial weights of crime	0.003	**	0.000	0.003	**	0.000	0.003	**	0.000	0.003	**	0.000	0.003	**	0.000
Wave 2 (2010-2013)	-0.296	**	0.004	-0.291	**	0.004	-0.291	**	0.004	-0.319	**	0.004	-0.323	**	0.004
Wave 3 (2017-2021)	-1.303	**	0.006	-1.265	**	0.007	-1.266	**	0.007	-1.304	**	0.007	-1.319	**	0.007
Mediators															
Stable family				-0.113	**	0.004	-0.113	**	0.004	-0.103	**	0.004	-0.104	**	0.004
Multigenerational family							-0.000		0.001	0.000		0.001	0.002	*	0.001
Consumer-facing local business (per capita)										0.017	**	0.000	0.017	**	0.000
% Self-employed													0.009	**	0.000
City-level random intercept variance	0.000		0.002	0.000		0.002	0.000		0.002	0.000		0.002	0.000		0.002
Constant	-4.832	**	0.012	-4.798	**	0.012	-4.797	**	0.012	-4.803	**	0.012	-4.933	**	0.014

N = 11,115 tracts within 18 cities for three waves (3,705 tracts per wave); ** p<0.01, * p<0.05.

City and Wave dummies are included in regressions but not shown in the table.

Table 7a. Temporal ordered panel mediation analysis using Poisson model with city and wave fixed effect for Stable Family

	Violent Crime			Burglary		
	b		*se*	*b*		*se*
Direct effect						
Immigrant Prevalence → Crime	0.081	**	0.029	-0.046		0.036
Immigrant Prevalence → Stable Family	0.076	**	0.025	0.076	**	0.025
Stable Family → Crime	-0.267	**	0.030	-0.129	*	0.050
Indirect effect						
Immigrant Prevalence → Stable Family → Crime	-0.020	**	0.008	-0.010		0.006
Total effect						
Immigrant Prevalence	0.061		0.033	-0.056		0.032

Note: * p < .05 two-tailed; **p < .01 two-tailed; controls included.

Immigrant prevalence is at t-1 and mediator is at t-2.

Table 7b. Temporal ordered panel mediation analysis using multi-level Poisson model for Multigenerational Family

	Violent Crime			Burglary	
	b		*se*	*b*	*se*
Direct effect					
Immigrant Prevalence → Crime	-0.010		0.051	-0.052	0.034
Immigrant Prevalence → Multigenerational Family	0.064		0.117	0.046	0.067
Multigenerational Family → Crime	0.007	*	0.003	0.005	0.004
Indirect effect					
Immigrant Prevalence → Multigenerational Family → Crime	0.001		0.001	0.001	0.001
Total effect					
Immigrant Prevalence	-0.010		0.051	-0.052	0.035

Note: * p < .05 two-tailed; **p < .01 two-tailed; controls included.

Immigrant prevalence is at t-1 and mediator is at t-2.

Table 7c. Temporal ordered panel mediation analysis using Poisson model with city and wave fixed effect for consumer-facing local business

	Violent Crime			Burglary		
	b		*se*	*b*		*se*
Direct effect						
Immigrant Prevalence → Crime	0.055	*	0.022	-0.059		0.037
Immigrant Prevalence → Business	0.236		0.241	0.236		0.241
Business → Crime	0.026	**	0.007	0.018	**	0.002
Indirect effect						
Immigrant Prevalence → Business → Crime	0.006		0.007	0.004		0.005
Total effect						
Immigrant Prevalence	0.061	**	0.023	-0.054		0.034

Note: * p < .05 two-tailed; **p < .01 two-tailed; controls included.

Immigrant prevalence is at t-1 and mediator is at t-2.

Table 7d. Temporal ordered panel mediation analysis using multi-level Poisson model for self-employment

	Violent Crime			Burglary		
	b		*se*	*b*		*se*
Direct effect						
Immigrant Prevalence → Crime	0.059	*	0.030	-0.051		0.034
Immigrant Prevalence → self-employment	-0.009		0.095	-0.009		0.095
self-employment → Crime	0.001		0.002	0.008	*	0.004
Indirect effect						
Immigrant Prevalence → self-employment → Crime	-0.001		0.001	-0.001		0.001
Total effect						
Immigrant Prevalence	0.059	*	0.030	-0.051		0.034

Note: * p < .05 two-tailed; **p < .01 two-tailed; controls included.

Immigrant prevalence is at t-1 and mediator is at t-2.

Table 8a. Temporal ordered panel mediation analysis using Poisson model with city and wave fixed effect for all mediators - Violent Crime

	Model 1			Model 2			Model 3			Model 4		
	b		*se*	*b*		*se*	*b*		*se*	*b*		*se*
Direct effect												
Immigrant Prevalence → Crime	0.081	**	0.029	0.082	**	0.030	0.078	**	0.024	0.078	**	0.024
Indirect effect												
Immigrant Prevalence → Stable Family → Crime	-0.020	**	0.008	-0.020	**	0.008	-0.020	*	0.008	-0.020	*	0.008
Immigrant Prevalence → Multigenerational Family → Crime				0.001		0.001	0.001		0.001	0.001		0.001
Immigrant Prevalence → Business → Crime							0.006		0.007	0.006		0.007
Immigrant Prevalence → self-employment → Crime										-0.001		0.000
Total Indirect effect				-0.020	**	0.008	-0.014		0.014	-0.014		0.014
Total effect												
Immigrant Prevalence	0.061		0.033	0.061		0.034	0.064	*	0.028	0.064	*	0.028

Note: * p < .05 two-tailed; **p < .01 two-tailed; controls included.

Immigrant prevalence is at t-1 and mediator is at t-2.

Table 8b. Temporal ordered panel mediation analysis using Poisson model with city and wave fixed effect for all mediators - Burglary

	Model 1		Model 2		Model 3		Model 4	
	b	*se*	*b*	*se*	*b*	*se*	*b*	*se*
Direct effect								
Immigrant Prevalence → Crime	-0.046	0.036	-0.046	0.036	-0.054	0.039	-0.053	0.038
Indirect effect								
Immigrant Prevalence → Stable Family → Crime	-0.010	0.006	-0.010	0.006	-0.010	0.006	-0.011	0.006
Immigrant Prevalence → Multigenerational Family → Crime			0.001	0.001	0.001	0.001	0.001	0.001
Immigrant Prevalence → Business → Crime					0.004	0.005	0.004	0.005
Immigrant Prevalence → self-employment → Crime							-0.001	0.000
Total Indirect effect			-0.010	0.006	-0.005	0.010	-0.006	0.010
Total effect								
Immigrant Prevalence	-0.056	0.032	-0.056	0.032	-0.060	0.032	-0.059	0.032

Note: * p < .05 two-tailed; **p < .01 two-tailed; controls included.

Immigrant prevalence is at t-1 and mediator is at t-2.

Appendix A: Wave 3 Crime Data Availability by City by Year

Austin, TX																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	x
Rape		x	x	x	x	x	x	x	x	x	x	x	x	x									
Robbery	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	x
Agg. Assault	x		x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	
Burglary	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	x
Larceny	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	x
MVT	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	x

Bellevue, WA																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x									x	x	x	x	x			x	x	x	x	x
Rape	x	x																					
Robbery	x	x	x									x	x	x	x				x	x	x	x	x
Agg. Assault												x		x	x				x			x	
Burglary	x	x	x									x	x	x	x				x	x	x	x	x
Larceny	x	x	x									x	x	x	x				x	x	x	x	x
MVT												x	x	x	x					x	x	x	x

Boston, MA																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x						x	x	x	x	x	x	x				x			x	
Rape	x	x	x							x	x	x		x	x				x	x	x	x	x
Robbery	x	x	x						x	x	x	x	x	x	x					x			
Agg. Assault	x	x	x						x	x	x	x	x	x	x								
Burglary	x	x	x						x	x	x	x	x	x	x				x	x	x		
Larceny	x	x	x						x	x	x	x	x	x	x				x	x	x	x	
MVT	x	x	x						x	x	x	x	x	x	x								

Buffalo, NY																								
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x									x	x	x	x	x			x	x		x	x
Rape	x	x	x									x	x	x	x								
Robbery	x	x	x									x	x	x	x	x			x	x		x	x
Agg. Assault	x	x	x									x	x	x	x	x							
Burglary	x	x	x									x	x	x	x	x			x	x			
Larceny	x	x	x									x	x	x	x	x			x	x		x	x
MVT	x	x										x	x	x	x	x							

Chandler, AZ																								
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder			x	x								x	x			x	x		x	x	x	x	x
Rape			x	x								x	x			x	x						
Robbery			x	x								x	x			x	x				x		x
Agg. Assault			x									x	x			x	x						
Burglary			x	x								x	x			x	x						
Larceny			x	x								x	x			x	x						
MVT			x	x								x	x			x	x		x	x	x	x	

Charlotte, NC																								
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x				x	x	x	x		x	x	x	x				x	x		x	x
Rape	x	x	x				x		x	x	x	x	x	x	x								
Robbery	x	x	x				x	x	x	x	x	x	x	x	x				x	x	x	x	x
Agg. Assault	x	x	x								x			x									
Burglary	x	x	x				x	x	x	x	x	x	x	x	x				x		x	x	x
Larceny	x	x	x				x	x	x	x	x	x	x	x	x				x	x	x	x	x
MVT	x	x	x				x	x	x	x	x	x	x	x	x				x	x	x	x	x

Chicago, IL																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder		x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	x
Rape																							
Robbery		x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	x
Agg. Assault		x	x	x	x	x	x	x	x	x	x	x	x	x									x
Burglary		x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	x
Larceny		x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x		x
MVT		x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	x
Note: No 2021 UCR report avalible for reliability check																							

Cincinnati, OH																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x		x									x	x	x	x								
Rape			x																				
Robbery			x									x	x	x	x								
Agg. Assault		x	x																x	x			
Burglary	x	x	x									x	x	x	x				x	x		x	
Larceny	x	x	x									x	x	x	x								
MVT	x	x	x									x	x	x	x								

Dallas, TX																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x								
Rape				x	x	x	x	x	x	x	x	x	x	x									
Robbery	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					x		x	x
Agg. Assault	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x								
Burglary	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x		x
Larceny	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	x
MVT	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x								

Denver, CO																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x											x	x				x		x	x	x
Rape	x	x	x									x	x	x									
Robbery	x	x	x									x	x		x				x	x	x	x	x
Agg. Assault	x	x	x									x	x	x	x				x				
Burglary	x	x	x									x	x	x	x				x	x	x	x	x
Larceny	x	x	x									x	x	x	x				x	x	x	x	x
MVT	x	x	x									x	x	x	x				x	x	x	x	x

Fort Worth, TX																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x		x	x	x	x	x	x	x	x	x	x	x								
Rape	x	x	x																				
Robbery	x	x	x		x	x	x	x	x	x	x	x	x	x	x								
Agg. Assault	x	x	x		x	x		x	x	x	x	x	x	x	x								
Burglary	x	x	x		x	x	x	x	x	x	x	x	x	x	x							x	x
Larceny	x	x	x		x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	x
MVT	x	x			x	x	x	x	x	x	x	x	x	x	x				x		x	x	x

Hartford, CT																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x				x	x	x	x	x	x	x	x	x				x	x	x	x	
Rape	x	x	x									x											
Robbery	x	x	x				x	x	x	x	x	x	x	x	x				x	x	x	x	
Agg. Assault	x	x	x				x	x	x	x	x	x		x	x				x	x	x	x	
Burglary	x	x	x				x	x	x	x	x	x	x	x	x				x	x	x	x	
Larceny	x	x	x				x	x	x	x	x	x	x	x	x				x	x	x	x	
MVT	x	x	x				x	x	x	x	x	x	x	x	x								

Kansas City, MO																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x	x	x	x	x	x		x	x	x	x	x	x								
Rape	x	x	x	x	x	x		x		x	x	x	x	x									
Robbery	x	x	x	x	x	x	x	x		x	x	x	x	x	x								
Agg. Assault	x	x	x	x	x	x	x	x		x	x	x	x	x	x								
Burglary	x	x	x	x	x	x	x	x		x	x	x	x	x	x								
Larceny	x	x	x	x	x	x	x	x		x	x	x	x	x	x								x
MVT	x	x	x	x	x	x	x	x		x	x	x	x	x	x								

Los Angeles, CA																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x												x	x			x	x	x	x	x
Rape															x	x							
Robbery	x	x	x												x	x			x	x	x	x	x
Agg. Assault	x	x	x												x	x			x	x	x	x	x
Burglary	x	x	x												x	x			x	x	x	x	x
Larceny	x	x	x												x	x							x
MVT	x	x	x												x	x			x	x	x	x	x
Note: No 2021 UCR report avalible for reliability check																							

Milwaukee, WI																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x				x	x	x	x	x	x	x	x	x				x	x	x	x	x
Rape		x	x						x	x	x	x	x	x									
Robbery	x	x	x				x	x	x	x	x	x	x	x	x				x	x	x	x	
Agg. Assault	x	x	x				x	x	x	x	x	x	x										
Burglary	x	x	x				x	x	x	x	x	x	x	x	x				x	x	x	x	x
Larceny	x	x	x				x																
MVT	x	x	x				x	x	x	x	x	x	x	x	x				x	x	x	x	

Minneapolis, MN																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x						x	x	x	x	x		x	x						x	x	x
Rape	x	x						x	x	x	x	x	x	x									
Robbery	x	x						x	x	x	x	x	x	x	x						x	x	x
Agg. Assault													x	x	x								
Burglary	x	x						x	x	x	x	x	x	x	x						x	x	x
Larceny	x	x						x	x	x	x	x	x	x	x						x	x	x
MVT	x	x						x	x	x	x	x	x	x	x						x	x	x
Note: For 2019, figures are not comparable to previous years' data due to changes in the state/local agency's reporting practices.																							

Portland, OR																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x	x	x	x	x	x		x	x	x	x	x	x								
Rape	x	x	x	x	x	x	x	x	x		x			x	x								
Robbery	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x		x
Agg. Assault	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x								
Burglary	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x		
Larceny	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	x
MVT	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	x

Rockford, IL																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x						x	x	x	x	x	x	x	x	x	x	x	x	x		
Rape																							
Robbery	x	x	x						x	x	x	x	x	x	x	x	x	x	x	x	x		
Agg. Assault		x																					
Burglary	x	x	x						x	x	x	x	x	x	x	x	x	x	x	x	x		
Larceny	x	x	x						x	x	x	x	x	x	x	x	x	x	x	x	x		
MVT	x	x	x														x	x	x				

Santa Rosa, CA																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x									x	x	x	x				x	x	x		
Rape	x	x	x									x	x	x	x								
Robbery	x	x	x									x	x	x	x				x	x	x		
Agg. Assault	x	x	x										x										
Burglary	x	x	x									x	x	x	x				x	x	x		
Larceny	x	x	x									x	x	x	x				x				
MVT	x	x	x									x	x	x	x				x				

Seattle, WA																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x							x	x	x	x	x	x	x	x						
Rape	x	x	x							x	x	x	x	x									
Robbery	x	x	x							x	x	x	x	x	x	x	x		x	x			
Agg. Assault	x	x	x							x	x	x	x	x	x	x	x				x		
Burglary	x	x	x							x	x	x	x	x	x	x	x		x	x	x	x	x
Larceny	x	x	x							x	x	x	x	x	x	x	x		x	x	x	x	x
MVT	x	x	x							x	x	x	x	x	x	x	x		x	x	x	x	x

St. Louis, MO																							
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Murder	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	
Rape	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x						
Robbery	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	
Agg. Assault	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	
Burglary	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	
Larceny	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	
MVT	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	

Appendix B: Comparison of Descriptive Statistics of NNCS3-P and NNCS2-P

Appendix B. Comparison of Descriptive Statistics for Neighborhood Crime and Structural Characteristics between NNCS3-P and NNCS2-P

	Wave 1 (1999-2001)								Wave 2 (2010 - 2013)							
	NNCS3-P (18 cities)				NNCS2-P (76 cities)				NNCS3-P (18 cities)				NNCS2-P (76 cities)			
	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
Dependent Variables																
Average Violent crime count (Homicide & Robbery)	17.27	17.75	0.00	204.00	13.58	15.41	0.00	204.00	12.08	12.99	0.00	148.00	11.12	12.47	0.00	148.00
Average Burglary crime count	37.34	27.86	0.00	311.00	38.44	29.59	0.00	408.00	31.43	26.17	0.00	215.00	35.29	27.89	0.00	215.00
Independent Variable																
Immigrant prevalence																
% Foreign-born	22.45	18.29	0.00	79.11	17.73	17.03	0.00	83.78	22.59	17.15	0.00	78.26	18.85	16.27	0.00	86.73
% New immigrants	10.17	9.43	0.00	57.30	8.06	8.66	0.00	57.30	7.73	7.31	0.00	43.75	6.68	6.96	0.00	54.37
% Linguistic isolation	10.84	12.40	0.00	72.99	8.32	11.18	0.00	72.99	10.96	12.50	0.00	80.00	8.80	11.42	0.00	81.10
Mediators																
Stable family																
% Married-couple family	38.45	15.53	0.00	90.55	41.64	17.05	0.00	95.25	34.52	15.31	0.00	89.88	37.01	16.73	0.00	95.94
% Children living in married-couple family	63.98	20.94	0.00	100.00	64.73	20.83	0.00	100.00	56.57	24.39	0.00	100.00	56.70	24.02	0.00	100.00
% Multigenerational family	5.25	4.28	0.00	27.82	4.84	3.93	0.00	42.96	4.39	4.18	0.00	39.82	4.30	3.93	0.00	39.82
Local customer facing business rate per 1000	1.49	2.74	0.00	58.51	1.46	2.82	0.00	85.86	3.80	5.47	0.00	85.52	3.79	5.58	0.00	98.33
% Self-employed	8.82	5.89	0.00	46.76	8.36	5.15	0.00	46.76	9.88	6.89	0.00	76.54	9.06	6.15	0.00	76.54
Control Variables																
Disadvantage	0.10	0.90	-1.60	3.68	0.01	0.87	-1.60	3.68	0.04	0.86	-1.59	3.17	0.01	0.84	-1.73	3.17
% Joblessness	34.71	13.11	5.01	78.98	33.10	12.68	5.01	78.98	33.74	12.06	6.01	79.96	33.85	12.02	5.06	83.62
% Professional workers	33.09	17.72	0.00	80.00	32.76	16.67	0.00	86.48	35.91	19.48	0.00	91.94	34.84	18.23	0.00	91.94

Appendix B. Comparison of Descriptive Statistics for Neighborhood Crime and Structural Characteristics between NNCS3-P and NNCS2-P

	Wave 1 (1999-2001)								Wave 2 (2010 - 2013)							
	NNCS3-P (18 cities)				NNCS2-P (76 cities)				NNCS3-P (18 cities)				NNCS2-P (76 cities)			
% Highschool graduates	72.59	19.41	14.12	100.00	75.68	18.06	14.12	100.00	79.48	16.48	25.25	100.00	81.41	15.15	23.59	100.00
% Female-headed households	16.85	11.87	0.00	80.41	16.08	11.05	0.00	96.06	17.40	12.31	0.00	70.82	17.02	11.40	0.00	93.46
% Secondary sector workers	18.27	8.69	0.00	68.82	17.96	8.64	0.00	68.82	22.03	11.12	0.00	66.22	21.68	10.95	0.00	71.49
% Population lives under poverty line	19.26	13.44	0.00	79.71	17.64	13.53	0	82.15	22.33	14.57	0.00	87.49	21.38	15.13	0.00	90.68
Residential instability	0.12	0.85	-1.93	2.64	0.00	0.86	-2.18	2.64	0.11	0.86	-1.83	3.75	0.00	0.88	-1.90	3.96
% Renter occupied housing units	55.42	24.59	0.00	100.00	48.69	25.08	0.00	100.00	55.60	23.84	0.00	100.00	50.23	24.01	0.00	100.00
% Recent movers 5 years older	51.73	13.72	13.20	99.03	52.09	14.25	13.20	100.00	18.51	10.32	0.00	74.91	18.52	10.25	0.00	78.42
Foreclosure Rate per 1,000	4.26	6.21	0.00	74.83	4.26	15.69	0.00	809.40	12.02	18.96	0.00	957.00	14.88	18.97	0.00	957.00
% Young male (15-34)	16.97	5.99	2.38	50.22	16.02	5.64	0.00	50.48	16.63	6.24	0.00	51.53	15.91	6.00	0.00	55.59
% Vacant housing	6.75	5.56	0.00	40.94	7.03	5.77	0.00	48.59	10.75	8.17	0.00	71.08	11.31	8.40	0.00	71.08
White Neighborhood	0.30	0.46	0.00	1.00	0.37	0.48	0.00	1.00	0.24	0.43	0.00	1.00	0.27	0.45	0.00	1.00
African American Neighborhood	0.14	0.35	0.00	1.00	0.12	0.33	0.00	1.00	0.13	0.34	0.00	1.00	0.12	0.32	0.00	1.00
Hispanic Neighborhood	0.11	0.31	0.00	1.00	0.08	0.27	0.00	1.00	0.13	0.34	0.00	1.00	0.10	0.30	0.00	1.00
Minority Neighborhood	0.09	0.29	0.00	1.00	0.07	0.25	0.00	1.00	0.10	0.31	0.00	1.00	0.09	0.28	0.00	1.00
Multi-ethnic Neighborhood	0.36	0.48	0.00	1.00	0.36	0.48	0.00	1.00	0.39	0.49	0.00	1.00	0.42	0.49	0.00	1.00
Violent crime spatial weights	5.30	4.36	0.00	48.89	13.58	15.41	0.00	204.00	3.75	3.29	0.00	29.62	3.37	3.16	0.00	29.62
Burglary spatial weights	11.16	6.64	0.77	70.76	11.41	7.10	0.32	107.00	9.15	5.95	0.10	36.14	10.23	6.91	0.10	48.88

Note: The NNCS3-P Sample has 3,705 census tracts across 18 cities; The NNCS2-P sample has 8,242 census tracts across 76 cities.

Appendix C: Correlation Matrices

Table C1: Matrix of correlations of NNCS3-P Wave 1

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1) Average Violent crime count (Homicide & Robbery)	1.00																		
(2) Average Violent crime count (Homicide & Robbery)	0.60	1.00																	
(3) Violent crime spatial weights	0.50	0.25	1.00																
(4) Burglary spatial weights	0.29	0.52	0.60	1.00															
(5) Immigrant prevalence	0.07	-0.15	-0.05	-0.28	1.00														
(6) Stable family	-0.44	-0.30	-0.47	-0.35	0.24	1.00													
(7) Multigenerational family	0.34	0.13	0.32	0.06	0.17	-0.20	1.00												
(8) Local customer facing business rate per 1000	0.16	0.11	0.11	0.11	-0.05	-0.09	-0.14	1.00											
(9) % Self-employed	-0.27	-0.21	-0.25	-0.22	-0.03	0.41	-0.38	-0.01	1.00										
(10) Disadvantage	0.49	0.20	0.43	0.15	0.35	-0.45	0.75	-0.13	-0.49	1.00									
(11) Residential instability	0.20	0.07	0.13	0.07	0.36	-0.47	-0.17	0.11	-0.19	0.14	1.00								
(12) Foreclosure	0.18	0.05	0.17	-0.01	0.04	0.01	0.44	-0.08	-0.13	0.33	-0.22	1.00							
(13) % Young males (15-34)	0.02	0.04	-0.02	0.01	0.34	-0.15	-0.18	0.12	-0.21	-0.07	0.70	-0.14	1.00						
(14) % Vacant housing	0.42	0.30	0.48	0.40	-0.21	-0.56	0.25	0.09	-0.24	0.43	0.20	0.13	-0.07	1.00					
(15) White neighborhood	-0.39	-0.17	-0.30	-0.07	-0.37	0.30	-0.56	0.07	0.38	-0.65	-0.17	-0.22	-0.06	-0.21	1.00				
(16) African American neighborhood	0.38	0.20	0.41	0.23	-0.38	-0.54	0.46	-0.03	-0.28	0.42	-0.13	0.14	-0.31	0.44	-0.26	1.00			
(17) Hispanic neighborhood	0.05	-0.10	0.02	-0.14	0.55	0.20	0.33	-0.07	-0.11	0.38	0.08	0.13	0.16	-0.05	-0.23	-0.14	1.00		
(18) Minority neighborhood	0.16	0.09	0.10	0.02	0.13	-0.07	0.25	-0.08	-0.11	0.28	0.03	0.27	-0.01	0.08	-0.21	-0.13	-0.11	1.00	
(19) Multi-ethnic neighborhood	-0.03	0.03	-0.08	-0.02	0.20	0.02	-0.16	0.04	-0.02	-0.11	0.19	-0.15	0.18	-0.13	-0.49	-0.30	-0.26	-0.24	1.00

Table C2: Matrix of correlations of NNCS3-P Wave 2

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1) Average Violent crime count (Homicide & Robbery)	1.00																		
(2) Average Violent crime count (Homicide & Robbery)	0.57	1.00																	
(3) Violent crime spatial weights	0.53	0.28	1.00																
(4) Burglary spatial weights	0.38	0.60	0.64	1.00															
(5) Immigrant prevalence	-0.06	-0.21	-0.21	-0.37	1.00														
(6) Stable family	-0.50	-0.30	-0.51	-0.38	0.13	1.00													
(7) Multigenerational family	0.26	0.15	0.24	0.08	0.18	-0.19	1.00												
(8) Local customer facing business rate per 1000	0.25	0.07	0.13	0.06	-0.09	-0.06	-0.13	1.00											
(9) % Self-employed	-0.29	-0.25	-0.35	-0.31	0.06	0.41	-0.25	-0.06	1.00										
(10) Disadvantage	0.45	0.23	0.40	0.20	0.32	-0.54	0.64	-0.16	-0.39	1.00									
(11) Residential instability	0.22	0.07	0.15	0.10	0.11	-0.49	-0.22	0.19	-0.19	0.05	1.00								
(12) Foreclosure	0.22	0.07	0.15	0.10	0.11	-0.49	-0.22	0.19	-0.19	0.05	1.00	1.00							
(13) % Young males (15-34)	0.07	0.00	0.03	0.01	0.18	-0.22	-0.14	0.15	-0.20	-0.04	0.64	0.64	1.00						
(14) % Vacant housing	0.36	0.21	0.43	0.34	-0.20	-0.46	0.07	0.09	-0.11	0.24	0.29	0.29	0.07	1.00					
(15) White neighborhood	-0.30	-0.18	-0.23	-0.09	-0.36	0.35	-0.44	0.07	0.28	-0.60	-0.05	-0.05	-0.04	-0.10	1.00				
(16) African American neighborhood	0.45	0.30	0.53	0.40	-0.38	-0.52	0.29	0.05	-0.26	0.40	0.00	0.00	-0.18	0.44	-0.22	1.00			
(17) Hispanic neighborhood	-0.01	-0.13	-0.05	-0.19	0.49	0.11	0.36	-0.12	-0.03	0.40	-0.11	-0.11	0.04	-0.16	-0.22	-0.15	1.00		
(18) Minority neighborhood	0.14	0.15	0.04	0.03	0.14	-0.14	0.18	-0.07	-0.14	0.28	0.00	0.00	-0.01	-0.02	-0.19	-0.13	-0.13	1.00	
(19) Multi-ethnic neighborhood	-0.13	-0.06	-0.16	-0.09	0.15	0.07	-0.17	0.03	0.05	-0.20	0.12	0.12	0.13	-0.10	-0.45	-0.31	-0.31	-0.28	1.00

Table C3: Matrix of correlations of NNCS3-P Wave 3

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1) Average Violent crime count (Homicide & Robbery)	1.00																		
(2) Average Violent crime count (Homicide & Robbery)	0.16	1.00																	
(3) Violent crime spatial weights	0.76	0.01	1.00																
(4) Burglary spatial weights	0.02	0.73	0.04	1.00															
(5) Immigrant prevalence	0.11	-0.14	0.12	-0.18	1.00														
(6) Stable family	-0.27	-0.16	-0.28	-0.14	0.10	1.00													
(7) Multigenerational family	0.19	-0.12	0.24	-0.15	0.23	-0.08	1.00												
(8) Local customer facing business rate per 1000	0.28	0.33	0.25	0.28	-0.11	-0.06	-0.18	1.00											
(9) % Self-employed	-0.02	-0.07	-0.03	-0.08	0.14	0.42	-0.13	-0.09	1.00										
(10) Disadvantage	0.28	-0.06	0.31	-0.09	0.29	-0.55	0.55	-0.20	-0.31	1.00									
(11) Residential instability	0.11	0.22	0.08	0.19	0.10	-0.48	-0.26	0.18	-0.22	0.00	1.00								
(12) Foreclosure	-0.05	-0.17	0.01	-0.10	-0.04	-0.00	0.07	-0.02	0.00	0.11	-0.10	1.00							
(13) % Young males (15-34)	0.05	0.14	0.03	0.12	0.15	-0.23	-0.16	0.14	-0.20	-0.10	0.64	-0.08	1.00						
(14) % Vacant housing	0.17	0.11	0.16	0.07	-0.21	-0.45	-0.04	0.12	-0.15	0.24	0.29	0.05	0.07	1.00					
(15) White neighborhood	-0.21	0.03	-0.24	0.08	-0.37	0.34	-0.35	0.08	0.22	-0.53	-0.07	-0.03	-0.06	-0.09	1.00				
(16) African American neighborhood	0.25	0.06	0.28	0.06	-0.35	-0.49	0.14	0.07	-0.28	0.40	0.01	0.07	-0.16	0.44	-0.17	1.00			
(17) Hispanic neighborhood	0.12	-0.16	0.16	-0.19	0.43	0.08	0.44	-0.13	0.00	0.38	-0.16	0.06	0.02	-0.17	-0.19	-0.13	1.00		
(18) Minority neighborhood	0.11	-0.05	0.10	-0.07	0.11	-0.18	0.19	-0.07	-0.11	0.30	-0.01	0.02	-0.07	0.02	-0.17	-0.12	-0.13	1.00	
(19) Multi-ethnic neighborhood	-0.14	0.08	-0.16	0.07	0.16	0.10	-0.22	0.03	0.06	-0.28	0.16	-0.07	0.18	-0.10	-0.45	-0.32	-0.35	-0.32	1.00

Bibliography

Abramitzky, R., & Boustan, L. (2022). *Streets of Gold: America's Untold Story of Immigrant Success*. PublicAffairs.

Abrego, L. J., & Gleeson, S. (2014). Workers, Families, and Immigration Policies. In T. Payan & E. de la Garza (Eds.), *Undecided Nation: Political Gridlock and the Immigration Crisis* (pp. 209–228). Springer International Publishing. https://doi.org/10.1007/978-3-319-06480-2_10

Azoulay, P., Jones, B. F., Kim, J. D., & Miranda, J. (2022). Immigration and Entrepreneurship in the United States. *American Economic Review: Insights, 4*(1), 71–88. https://doi.org/10.1257/aeri.20200588

Bankston, C. L. (2014). *Immigrant Networks and Social Capital*. John Wiley & Sons.

Bardis, P. D. (1959). A familism scale. *Marriage & Family Living*.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

Barranco, R. E., & Shihadeh, E. S. (2015). Walking ATMs and the immigration spillover effect: The link between Latino immigration and robbery victimization. *Social Science Research, 52*, 440–450. https://doi.org/10.1016/j.ssresearch.2015.03.003

Bates, T., Bradford, W. D., & Seamans, R. (2018). Minority entrepreneurship in twenty-first century America. *Small Business Economics, 50*(3), 415–427. https://doi.org/10.1007/s11187-017-9883-5

Baumer, E. P., Wolff, K. T., & Arnio, A. N. (2012). A Multicity Neighborhood Analysis of Foreclosure and Crime. *Social Science Quarterly, 93*(3), 577–601. https://doi.org/10.1111/j.1540-6237.2012.00888.x

Beck, R. H. (1996). *The case against immigration: The moral, economic, social, and environmental reasons for reducing US immigration back to traditional levels*. Roy Beck.

Blau, J. R., & Blau, P. M. (1982). The cost of inequality: Metropolitan structure and violent crime. *American Sociological Review*, 114–129.

Brantingham, P. L., & Brantingham, P. J. (1984). *Patterns in crime*. Macmillan.

Brantingham, P. L., & Brantingham, P. J. (1993). Nodes, paths and edges: Considerations on the complexity of crime and the physical environment. *Journal of Environmental Psychology*, *13*(1), 3–28. https://doi.org/10.1016/S0272-4944(05)80212-9

Brantingham, P. L., & Brantingham, P. J. (1995). Criminality of place. *European Journal on Criminal Policy and Research*, *3*(3), 5–26. https://doi.org/10.1007/BF02242925

Breton, R. (1964). Institutional Completeness of Ethnic Communities and the Personal Relations of Immigrants. *American Journal of Sociology*, *70*(2), 193–205. https://doi.org/10.1086/223793

Brooks, D. (2006, March 30). Opinion | Immigrants to Be Proud Of. *The New York Times*. https://www.nytimes.com/2006/03/30/opinion/immigrants-to-be-proud-of.html

Browning, C. R., Dietz, R. D., & Feinberg, S. L. (2004). The Paradox of Social Organization: Networks, Collective Efficacy, and Violent Crime in Urban Neighborhoods*. *Social Forces*, *83*(2), 503–534. https://doi.org/10.1353/sof.2005.0006

Budiman, A. (2020). *Key findings about U.S. immigrants*. Pew Research Center. https://www.pewresearch.org/short-reads/2020/08/20/key-findings-about-u-s-immigrants/

Budiman, A., Tamir, C., Mora, L., & Noe-Bustamante, L. (2020). *Facts on U.S. immigrants, 2018*. Pew Research Center. https://www.pewresearch.org/hispanic/2020/08/20/facts-on-u-s-immigrants/

Bursik, R. J. (1999). The Informal Control of Crime Through Neighborhood Networks. *Sociological Focus*, *32*(1), 85–97. https://doi.org/10.1080/00380237.1999.10571125

Bursik, R. J., & Grasmick, H. G. (1993). *Neighborhoods and Crime: The Dimensions of Effective Community Control*. Lexington Books.

Butcher, K. F., & Piehl, A. M. (1998). Cross-city evidence on the relationship between immigration and crime. *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management*, *17*(3), 457–493.

Calzada, E. J., Tamis-LeMonda, C. S., & Yoshikawa, H. (2013). Familismo in Mexican and Dominican Families From Low-Income,Urban Communities. *Journal of Family Issues*, *34*(12), 1696–1724. https://doi.org/10.1177/0192513X12460218

Camarota, S. A. (2011). *A record-setting decade of immigration, 2000 to 2010*. Center for Immigration Studies Washington, DC.

Casper, L. M., Florian, S., Potts, C., & Brandon, P. D. (2016). Portrait of American grandparent families. *Grandparenting in the United States*, 109–132.

Catanzarite, L., & Trimble, L. (2008). Latinos in the United States Labor Market. In H. Rodríguez, R. Sáenz, & C. Menjívar (Eds.), *Latinas/os in the United States: Changing the Face of América* (pp. 149–167). Springer US. https://doi.org/10.1007/978-0-387-71943-6_10

Chacko, E., & Price, M. (2015). Immigrant Entrepreneurship in the Washington Metropolitan Area: Opportunities and Challenges Facing Ethnic Minorities. In *The Housing and Economic Experiences of Immigrants in U.S. and Canadian Cities* (pp. 302–327). University of Toronto Press.

Cloward, R. A., & Ohlin, L. (1960). *Delinquency and Opportunity: A Theory of Delinquent Gangs.* Free Press.

Cohen, L. E., & Felson, M. (1979). Social Change and Crime Rate Trends: A Routine Activity Approach. *American Sociological Review*, *44*(4), 588–608. https://doi.org/10.2307/2094589

Cohn, D., Horowitz, J. M., Minkin, R., Fry, R., & Hurst, K. (2022). *Financial issues top the list of reasons US adults live in multigenerational homes*.

Coleman, J. S. (1990). *Foundations of social theory*. Harvard university press.

Contreras, C., & Hipp, J. R. (2020). Drugs, Crime, Space, and Time: A Spatiotemporal Examination of Drug Activity and Crime Rates. *Justice Quarterly*, *37*(2), 187–209. https://doi.org/10.1080/07418825.2018.1515318

Coy, P. (2022, July 11). Opinion | Why So Many Children of Immigrants Rise to the Top. *The New York Times*. https://www.nytimes.com/interactive/2022/07/11/opinion/immigrants-success-america.html

Crutchfield, R. D. (1989). Labor Stratification and Violent Crime*. *Social Forces*, *68*(2), 489–512. https://doi.org/10.1093/sf/68.2.489

Crutchfield, R. D., & Pitchford, S. R. (1997). Work and Crime: The Effects of Labor Stratification*. *Social Forces*, *76*(1), 93–118. https://doi.org/10.1093/sf/76.1.93

Delgado, M., Porter, M. E., & Stern, S. (2014). *Defining clusters of related industries.* National Bureau of Economic Research, Inc.

Dohan, D. (2003). *The Price of Poverty: Money, Work, and Culture in the Mexican American Barrio*. University of California Press.

Duck, W. (2015). *No Way Out: Precarious Living in the Shadow of Poverty and Drug Dealing*. University of Chicago Press.

Durand, J., & Massey, D. S. (2004). *Crossing the Border: Research from the Mexican Migration Project*. Russell Sage Foundation.

Espinoza-Kulick, M. A. V., Fennelly, M., & Beck, K. (2021). Ethnic Enclaves. In M. A. V. Espinoza-Kulick, M. Fennelly, & K. Beck, *Sociology*. Oxford University Press. https://doi.org/10.1093/obo/9780199756384-0257

Farrington, D. P. (2011). Families and crime. *Crime and Public Policy*, 130–157.

Farrington, D. P., & Loeber, R. (1999). Transatlantic replicability of risk factors in the development of delinquency. In *Historical and geographical influences on psychopathology* (pp. 299–329).

Feldmeyer, B., Madero-Hernandez, A., Rojas-Gaona, C. E., & Sabon, L. C. (2019). Immigration, Collective Efficacy, Social Ties, and Violence: Unpacking the Mediating Mechanisms in Immigration Effects on Neighborhood-Level Violence. *Race and Justice*, *9*(2), 123–150. https://doi.org/10.1177/2153368717690563

Felson, M., & Cohen, L. E. (1980). Human ecology and crime: A routine activity approach. *Human Ecology*, *8*(4), 389–406.

Foner, N. (2013). *One out of three: Immigrants in New York in the twenty-first century*. Columbia University Press.

Foner, N., & Dreby, J. (2011). Relations Between the Generations in Immigrant Families. *Annual Review of Sociology*, *37*. https://doi.org/10.1146/annurev-soc-081309-150030

Fong, E., & Berry, B. (2017). *Immigration and the City*. John Wiley & Sons.

Fry, R., & Passel, J. (2014, July 17). The Growth in Multi-generational Family Households. *Pew Research Center's Social & Demographic Trends Project*. https://www.pewresearch.org/social-trends/2014/07/17/the-growth-in-multi-generational-family-households/

Geoscape. (2106). *Hispanic Businesses and Entrepreneuers Drive Growth in the New Economy*. Geoscape. https://www.immigrationresearch.org/system/files/Geoscape_Hispanic_Business_Owners.pdf

Gotliboym, I. (2023). *Small Business Facts—An Analysis of Immigrant Employer Ownership*. U.S. Small Business Administration, Office of Advocacy.

Groff, E. R. (2011). Exploring 'near': Characterizing the spatial extent of drinking place influence on crime. *Australian & New Zealand Journal of Criminology*, *44*(2), 156–179. https://doi.org/10.1177/0004865811405253

Groff, E. R. (2014). Quantifying the Exposure of Street Segments to Drinking Places Nearby. *Journal of Quantitative Criminology*, *30*(3), 527–548. https://doi.org/10.1007/s10940-013-9213-2

Groff, E. R., & Lockwood, B. (2014). Criminogenic Facilities and Crime across Street Segments in Philadelphia: Uncovering Evidence about the Spatial Extent of Facility Influence. *Journal of Research in Crime and Delinquency*, *51*(3), 277–314. https://doi.org/10.1177/0022427813512494

Harris, C. T., & Feldmeyer, B. (2013). Latino immigration and White, Black, and Latino violent crime: A comparison of traditional and non-traditional immigrant destinations. *Social Science Research*, *42*(1), 202–216. https://doi.org/10.1016/j.ssresearch.2012.08.014

Hayes, A. F. (2017). *Introduction to Mediation, Moderation, and Conditional Process Analysis, Second Edition: A Regression-Based Approach*. Guilford Publications.

Hirschi, T. (1969). *Causes of Delinquency*. University of California Press.

Hunter, A. D. (1985). Private, parochial and public social orders: The problem of crime and incivility in urban communities. In *The challenge of social control: Institution building and systemic constraint*.

Iacobucci, D. (2008). *Mediation Analysis*. SAGE.

Jacobs, J. (1961). *The Death and Life of Great American Cities*. Vintage.

Judd, C. M., & Kenny, D. A. (1981). Process Analysis: Estimating Mediation in Treatment Evaluations. *Evaluation Review*, *5*(5), 602–619. https://doi.org/10.1177/0193841X8100500502

Kallick, D. D. (2012). *Immigrant Small Business Owners: A Significant and Growing Part of the Economy*. Fiscal Policy Institute, 2012.

Kamo, Y. (2000). Racial and Ethnic Differences in Extended Family Households. *Sociological Perspectives*, *43*(2), 211–229. https://doi.org/10.2307/1389794

Kane, K., Hipp, J. R., & Kim, J. H. (2017). Analyzing Accessibility Using Parcel Data: Is There Still an Access–Space Trade-Off in Long Beach, California?

The Professional Geographer, *69*(3), 486–503. https://doi.org/10.1080/00330124.2016.1266951

Kang, J., & Cohen, P. N. (2017). Extended kin and children's behavioral functioning: Family structure and parental immigrant status. *Social Science & Medicine*, *186*, 61–69. https://doi.org/10.1016/j.socscimed.2017.04.033

Kao, G. (2004). Social Capital and Its Relevance to Minority and Immigrant Populations. *Sociology of Education*, *77*(2), 172–175. https://doi.org/10.1177/003804070407700204

Keene, J. R., & Batson, C. D. (2010). Under One Roof: A Review of Research on Intergenerational Coresidence and Multigenerational Households in the United States. *Sociology Compass*, *4*(8), 642–657. https://doi.org/10.1111/j.1751-9020.2010.00306.x

Kim, Y.-A., & Hipp, J. R. (2022). Small Local versus Non-Local: Examining the Relationship between Locally Owned Small Businesses and Spatial Patterns of Crime. *Justice Quarterly*, *39*(5), 983–1008. https://doi.org/10.1080/07418825.2021.1879899

Kim, Y.-A., Hipp, J. R., & Kubrin, C. E. (2022). Immigrant Organizations and Neighborhood Crime. *Crime & Delinquency*, *68*(11), 1948–1976. https://doi.org/10.1177/00111287221084289

Kornhauser, R. R. (1978). *Social Sources of Delinquency: An Appraisal of Analytic Models*. University of Chicago Press.

Krivo, L. J., Lyons, C. J., & Vélez, M. B. (2021). The U.S. Racial Structure and Ethno-Racial Inequality in Urban Neighborhood Crime, 2010–2013. *Sociology of Race and Ethnicity*, *7*(3), 350–368. https://doi.org/10.1177/2332649220948551

Krivo, L. J., Lyons, C. J., & Velez, M. B. (2022). *National Neighborhood Crime Study, Wave 2 (NNCS2), [United States], 1999-2013*. Inter-university Consortium for Political and Social Research [distributor]. https://doi.org/10.3886/ICPSR38483.v2

Kubrin, C. E., & Desmond, S. A. (2015). The Power of Place Revisited: Why Immigrant Communities Have Lower Levels of Adolescent Violence. *Youth Violence and Juvenile Justice*, *13*(4), 345–366. https://doi.org/10.1177/1541204014547590

Kubrin, C. E., & Hipp, J. R. (2016). Do Fringe Banks Create Fringe Neighborhoods? Examining the Spatial Relationship between Fringe Banking and Neighborhood Crime Rates. *Justice Quarterly*, *33*(5), 755–784. https://doi.org/10.1080/07418825.2014.959036

Kubrin, C. E., & Ishizawa, H. (2012). Why some immigrant neighborhoods are safer than others: Divergent findings from Los Angeles and Chicago. *The Annals of the American Academy of Political and Social Science*, *641*(1), 148–173.

Kubrin, C. E., Kim, Y.-A., & Hipp, J. R. (2019). Institutional Completeness and Crime Rates in Immigrant Neighborhoods. *Journal of Research in Crime and Delinquency*, *56*(2), 175–212. https://doi.org/10.1177/0022427818799125

Kye, S. H. (2018). The Rise of Ethnoburbs. *Contexts*, *17*(4), 68–70. https://doi.org/10.1177/1536504218812874

Laub, J. H., & Sampson, R. J. (1993). Turning Points in the Life Course: Why Change Matters to the Study of Crime*. *Criminology*, *31*(3), 301–325. https://doi.org/10.1111/j.1745-9125.1993.tb01132.x

Lawler, E. J. (2001). An Affect Theory of Social Exchange. *American Journal of Sociology*, *107*(2), 321–352. https://doi.org/10.1086/324071

Lawler, E. J., & Yoon, J. (1998). Network Structure and Emotion in Exchange Relations. *American Sociological Review*, *63*(6), 871–894. https://doi.org/10.2307/2657506

Lee, L. (2023, January 4). Minority Business Ownership Differs by Sector. *Census.Gov/America Counts: Stories*. https://www.census.gov/library/stories/2023/01/who-owns-americas-businesses.html

Lee, M. T., & Martinez Jr., R. (2002). Social Disorganization Revisited: Mapping the Recent Immigration and Black Homicide Relationship in Northern Miami. *Sociological Focus*, *35*(4), 363–380. https://doi.org/10.1080/00380237.2002.10570709

Lee, M. T., Martinez, R., & Rosenfeld, R. (2001). Does Immigration Increase Homicide? Negative Evidence From Three Border Cities. *The Sociological Quarterly*, *42*(4), 559–580. https://doi.org/10.1111/j.1533-8525.2001.tb01780.x

Ley, D. (2008). The immigrant church as an urban service hub. *Urban Studies*, *45*(10), 2057–2074.

Lichter, D. T., Qian, Z., & Tumin, D. (2015). Whom Do Immigrants Marry? Emerging Patterns of Intermarriage and Integration in the United States. *The ANNALS of the American Academy of Political and Social Science*, *662*(1), 57–78. https://doi.org/10.1177/0002716215594614

Light, I., & Gold, S. J. (2000). *Ethnic Economies*. Emerald Group Publishing Limited.

Little, T. D. (2013). *Longitudinal structural equation modeling*. Guilford Press.

Lou, C., Adams, G., & Bernstein, H. (2019). Part of us: A data-driven look at children of immigrants. *Urban Institute*. https://www.urban.org/features/part-us-data-driven-look-children-immigrants

Lyons, C. J., Vélez, M. B., & Krivo, L. J. (2022). The Dynamic Racial Structure and Disparities in Neighborhood Crime Change. *Social Problems*, spac013. https://doi.org/10.1093/socpro/spac013

MacKinnon, D. P., Lockwood, C. M., Hoffman, J. M., West, S. G., & Sheets, V. (2002). *A Comparison of Methods to Test Mediation and Other Intervening Variable Effects*. *7*(1), 83–104. https://doi.org/hhttps://doi.org/10.1037/1082-989X.7.1.83

Marsiglia, F. F., Parsai, M., & Kulis, S. (2009). Effects of Familism and Family Cohesion on Problem Behaviors Among Adolescents in Mexican Immigrant Families in the Southwest United States. *Journal of Ethnic And Cultural Diversity in Social Work*, *18*(3), 203–220. https://doi.org/10.1080/15313200903070965

Martinez Jr., R., Stowell, J. I., & Lee, M. T. (2010). Immigration and Crime in an Era of Transformation: A Longitudinal Analysis of Homicides in San Diego Neighborhoods, 1980–2000*. *Criminology*, *48*(3), 797–829. https://doi.org/10.1111/j.1745-9125.2010.00202.x

Massey, D. S., & Mullan, B. P. (1984). Processes of Hispanic and Black Spatial Assimilation. *American Journal of Sociology*, *89*(4), 836–873. https://doi.org/10.1086/227946

Maxwell, S. E., & Cole, D. A. (2007). Bias in cross-sectional analyses of longitudinal mediation. *Psychological Methods*, *12*(1), 23–44. https://doi.org/10.1037/1082-989X.12.1.23

Maxwell, S. E., Cole, D. A., & Mitchell, M. A. (2011). Bias in Cross-Sectional Analyses of Longitudinal Mediation: Partial and Complete Mediation Under an Autoregressive Model. *Multivariate Behavioral Research*, *46*(5), 816–841. https://doi.org/10.1080/00273171.2011.606716

Mayol-García, Y., Gurrentz, B., & Kreider, R. M. (2021). *Number, Timing, and Duration of Marriages and Divorces: 2016*. US Department of Commerce.

McManus, M. (2016). *Minority Business Ownership: Data from the 2012 Survey of Business Owners*. *12*, 13.

Memon, M. A., Cheah, J.-H., Ramayah, T., Ting, H., & Chuah, F. (2018). Mediation Analysis Issues and Recommendations. *Journal of Applied Structural Equation Modeling*, *2*(1), i–ix. https://doi.org/10.47263/JASEM.2(1)01

Menjívar, C., Abrego, L. J., & Schmalzbauer, L. C. (2016). *Immigrant Families*. John Wiley & Sons.

Merton, R. K. (1938). Social Structure and Anomie. *American Sociological Review*, *3*, 672–682.

Morenoff, J. D., & Astor, A. (2006). Immigrant assimilation and crime. *Immigration and Crime: Race, Ethnicity, and Violence*, 36–63.

Morenoff, J. D., Sampson, R. J., & Raudenbush, S. W. (2001). Neighborhood Inequality, Collective Efficacy, and the Spatial Dynamics of Urban Violence*. *Criminology*, *39*(3), 517–558. https://doi.org/10.1111/j.1745-9125.2001.tb00932.x

National Academies of Sciences, E., & Population, C. on. (2016). *The integration of immigrants into American society*. National Academies Press.

Office of the New York State Comptroller. (2016). *An Economic Snapshot of the Greater Sunset Park Area*. Office of the State Deputy Comptroller for the City of New York.

O'Laughlin, K. D., Martin, M. J., & Ferrer, E. (2018). Cross-Sectional Analysis of Longitudinal Mediation Processes. *Multivariate Behavioral Research*, *53*(3), 375–402. https://doi.org/10.1080/00273171.2018.1454822

Olsen-Medina, K., & Batalova, J. (2020, September 15). College-Educated Immigrants in the United States. *Migrationpolicy.Org*. https://www.migrationpolicy.org/article/college-educated-immigrants-united-states

Orozco, M. (2020). Reconceptualizing the Enclave: Measuring Success Among Latino-Owned Businesses. *Social Science Quarterly*, *101*(4), 1374–1396. https://doi.org/10.1111/ssqu.12821

Osgood, D. W. (2000). Poisson-Based Regression Analysis of Aggregate Crime Rates. *Journal of Quantitative Criminology*, *16*(1), 21–43. https://doi.org/10.1023/A:1007521427059

Ousey, G. C., & Kubrin, C. E. (2009). Exploring the Connection between Immigration and Violent Crime Rates in U.S. Cities, 1980–2000. *Social Problems*, *56*(3), 447–473. https://doi.org/10.1525/sp.2009.56.3.447

Ousey, G. C., & Kubrin, C. E. (2018). Immigration and Crime: Assessing a Contentious Issue. *Annual Review of Criminology*, *1*(1), 63–84. https://doi.org/10.1146/annurev-criminol-032317-092026

Painter-Davis, N. (2016). Immigration Effects on Violence Contextualized: The Role of Immigrant Destination Type and Race/Ethnicity. *Sociological Perspectives*, *59*(1), 130–152. https://doi.org/10.1177/0731121415588152

Park, K. (1997). *The Korean American Dream: Immigrants and Small Business in New York City*. Cornell University Press.

Pattillo, M. E. (1998). *Sweet Mothers and Gangbangers: Managing Crime in a Black Middle-Class Neighborhood*. *76*(3), 747–774.

Pebley, A. R., & Rudkin, L. L. (1999). Grandparents Caring for Grandchildren: What Do We Know? *Journal of Family Issues*, *20*(2), 218–242. https://doi.org/10.1177/019251399020002003

Peterson, R. D., & Krivo, L. J. (2010a). *Divergent Social Worlds: Neighborhood Crime and the Racial-Spatial Divide*. Russell Sage Foundation.

Peterson, R. D., & Krivo, L. J. (2010b). *National Neighborhood Crime Study (NNCS), 2000: Version 1* (Version v1) [dataset]. ICPSR - Interuniversity Consortium for Political and Social Research. https://doi.org/10.3886/ICPSR27501.V1

Pew Research Center. (2013). *Second-generation Americans: A portrait of the adult children of immigrants*. Pew Research Center Washington, DC.

Pilkauskas, N. V., & Dunifon, R. E. (2016). Understanding Grandfamilies: Characteristics of Grandparents, Nonresident Parents, and Children. *Journal of Marriage and Family*, *78*(3), 623–633. https://doi.org/10.1111/jomf.12291

Pittman, L. D., Ioffe, M., & Keeports, C. R. (2016). Young Adults' Perceptions of Living with Their Grandparents During Childhood. In *Grandparenting in the United States* (pp. 185–206). Routledge New York, NY.

Porter, M. E. (2000). Location, Competition, and Economic Development: Local Clusters in a Global Economy. *Economic Development Quarterly*, *14*(1), 15–34. https://doi.org/10.1177/089124240001400105

Portes, A. (1981). Modes of Structural Incorporation and Present Theories of Labor Immigration. *International Migration Review*, *15*(1_suppl), 279–297.

Portes, A. (1998). Social Capital: Its Origins and Applications in Modern Sociology. *Annual Review of Sociology*, *24*(1), 1–24. https://doi.org/10.1146/annurev.soc.24.1.1

Portes, A., & Bach, R. L. (1985). Contrasting Histories: Cuban And Mexican Immigrants In The United States. In *Latin Journey* (pp. 72–110). University of California Press. https://doi.org/10.1525/9780520907317-006

Portes, A., & Rumbaut, R. G. (2006). *Immigrant America: A Portrait*. University of California Press.

Portes, A., & Stepick, A. (1993). *City on the edge: The transformation of Miami*. Univ of California Press.

Portes, P. A., & Rumbaut, P. R. G. (2001). *Legacies: The Story of the Immigrant Second Generation*. University of California Press.

Price, M., & Chacko, E. (2009). The Mixed Embeddedness of Ethnic Entrepreneurs in a New Immigrant Gateway. *Journal of Immigrant & Refugee Studies*, *7*(3), 328–346. https://doi.org/10.1080/15562940903150105

Putnam, R. (1993, April 1). The Prosperous Community: Social Capital and Public Life. *The American Prospect*. https://prospect.org/api/content/27753724-6757-5e80-925d-9542fc7ad4cb/

Ramey, D. M. (2013). Immigrant Revitalization and Neighborhood Violent Crime in Established and New Destination Cities. *Social Forces*, *92*(2), 597–629. https://doi.org/10.1093/sf/sot085

Ramos, J., Hernandez, C., & Shelfer, D. (2023). Illuminating the Immigration–Crime Nexus: A Test of the Immigration Revitalization Perspective. *Societies*, *13*(6), 137. https://doi.org/10.3390/soc13060137

Reid, L. W., Weiss, H. E., Adelman, R. M., & Jaret, C. (2005). The immigration–crime relationship: Evidence across US metropolitan areas. *Social Science Research*, *34*(4), 757–780. https://doi.org/10.1016/j.ssresearch.2005.01.001

Rosenfeld, M. J., & Tienda, M. (1999). Mexican Immigration, Occupational Niches, and Labor-Market Competition: Evidence from Los Angeles, Chicago. *Immigration and Opportunity: Race, Ethnicity, and Employment in the United States, Edited by Frank D. Bean and Stephanie Bell-Rose. New York: Russell Sage Foundation*, 64–105.

Sabogal, F., Marín, G., Otero-Sabogal, R., Marín, B. V., & Perez-Stable, E. J. (1987). Hispanic Familism and Acculturation: What Changes and What Doesn't? *Hispanic Journal of Behavioral Sciences*, *9*(4), 397–412. https://doi.org/10.1177/07399863870094003

Sampson, R. J. (1986). Neighborhood family structure and the risk of personal victimization. In *The social ecology of crime* (pp. 25–46). Springer.

Sampson, R. J., & Bean, L. (2006). Cultural Mechanisms and Killing Fields: A Revised Theory of Community-Level Racial Inequality. In *The many colors of crime* (pp. 8–36). New York University Press.

Sampson, R. J., & Groves, W. B. (1989). Community Structure and Crime: Testing Social-Disorganization Theory. *American Journal of Sociology*, *94*(4), 774–802. https://doi.org/10.1086/229068

Sampson, R. J., Morenoff, J. D., & Earls, F. (1999). Beyond Social Capital: Spatial Dynamics of Collective Efficacy for Children. *American Sociological Review*, *64*(5), 633–660. https://doi.org/10.2307/2657367

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science*, *277*(5328), 918–924.

Sanders, J. M., & Nee, V. (1996). Immigrant Self-Employment: The Family as Social Capital and the Value of Human Capital. *American Sociological Review*, *61*(2), 231–249. https://doi.org/10.2307/2096333

Sharkey, P. (2019). *Uneasy Peace: The Great Crime Decline, the Renewal of City Life, and the Next War on Violence*. National Geographic Books.

Shaw, C. R., & McKay, H. D. (1942). *Juvenile delinquency and urban areas* (pp. xxxii, 451). University of Chicago Press.

Shihadeh, E. S., & Barranco, R. E. (2010a). Latino Employment and Black Violence: The Unintended Consequence of U.S. Immigration Policy. *Social Forces*, *88*(3), 1393–1420. https://doi.org/10.1353/sof.0.0286

Shihadeh, E. S., & Barranco, R. E. (2010b). Latino Employment and Non-Latino Homicide in Rural Areas: The Implications of U.S. Immigration Policy. *Deviant Behavior*, *31*(5), 411–439. https://doi.org/10.1080/01639620903231274

Shrout, P. E. (2011). Commentary: Mediation Analysis, Causal Process, and Cross-Sectional Data. *Multivariate Behavioral Research*, *46*(5), 852–860. https://doi.org/10.1080/00273171.2011.606718

Shrout, P. E., & Bolger, N. (2002). Mediation in experimental and nonexperimental studies: New procedures and recommendations. *Psychological Methods*, *7*(4), 422–445. https://doi.org/10.1037/1082-989X.7.4.422

Sidebottom, A., & Wortley, R. (2015). Environmental Criminology. In *The Handbook of Criminological Theory* (pp. 156–181). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118512449.ch9

Silverstein, M., & Lee, Y. (2016). Race and Ethnic Differences in Grandchild Care and Financial Transfers with Grandfamilies: An Intersectional Resource

Approach. In *Grandparenting in the United States* (pp. 19–40). Routledge New York, NY.

Singer, A. (2004). *The rise of new immigrant gateways*. Center on Urban and Metropolitan Policy, The Brookings Institution.

Singer, A. (2015, December 1). Metropolitan immigrant gateways revisited, 2014. *Brookings*. https://www.brookings.edu/articles/metropolitan-immigrant-gateways-revisited-2014/

Stansfield, R. (2014). Safer Cities: A Macro-Level Analysis of Recent Immigration, Hispanic-Owned Businesses, and Crime Rates in the United States. *Journal of Urban Affairs*, *36*(3), 503–518. https://doi.org/10.1111/juaf.12051

Stritzel, H., Smith Gonzalez, C., Cavanagh, S. E., & Crosnoe, R. (2021). Family Structure and Secondary Exposure to Violence in the Context of Varying Neighborhood Risks and Resources. *Socius*, *7*, 2378023121992941. https://doi.org/10.1177/2378023121992941

Toby, J. (1957). Social Disorganization and Stake in Conformity: Complementary Factors in the Predatory Behavior of Hoodlums. *Journal of Criminal Law, Criminology and Police Science*, *48*(1), 12–17.

Valdez, Z. (2011). *The New Entrepreneurs: How Race, Class, and Gender Shape American Enterprise*. Stanford University Press.

Vallejo, J. A., & Canizales, S. L. (2016). Latino/a professionals as entrepreneurs: How race, class, and gender shape entrepreneurial incorporation. *Ethnic and Racial Studies*, *39*(9), 1637–1656. https://doi.org/10.1080/01419870.2015.1126329

Vélez, M. B. (2006). Toward an Understanding of the Lower Rates of Homicide in Latino versus Black Neighborhoods: A Look at Chicago. In *The Many Colors of Crime* (pp. 91–107). New York University Press. https://doi.org/10.18574/nyu/9780814768549-007

Vélez, M. B. (2009). Contextualizing the Immigration and Crime Effect: An Analysis of Homicide in Chicago Neighborhoods. *Homicide Studies*, *13*(3), 325–335. https://doi.org/10.1177/1088767909337238

Vélez, M. B. (2014). Informal Social Control. In G. Bruinsma & D. Weisburd (Eds.), *Encyclopedia of Criminology and Criminal Justice* (pp. 2490–2500). Springer. https://doi.org/10.1007/978-1-4614-5690-2_429

Waldinger, R. (1993). The ethnic enclave debate revisited. *International Journal of Urban and Regional Research*, *17*, 444–452.

Waldinger, R. (1997). Black/immigrant competition re-assessed: New evidence from Los Angeles. *Sociological Perspectives*, *40*(3), 365–386.

Wang, W. (2021, March 3). Immigrant Families Are More Stable. *Institute for Family Studies*. https://ifstudies.org/blog/immigrant-families-are-more-stable

Wikström, P.-O. H. (2009). *Routine Activity Theories* (pp. 9780195396607–0010) [dataset]. https://doi.org/10.1093/obo/9780195396607-0010

Williams, S. A., & Hipp, J. R. (2019). How great and how good?: Third places, neighbor interaction, and cohesion in the neighborhood context. *Social Science Research*, *77*, 68–78. https://doi.org/10.1016/j.ssresearch.2018.10.008

Wilson, K. L., & Portes, A. (1980). Immigrant Enclaves: An Analysis of the Labor Market Experiences of Cubans in Miami. *American Journal of Sociology*, *86*(2), 295–319. https://doi.org/10.1086/227240

Wilson, W. J. (1996). *When work disappears: The world of the new urban poor*. Knopf.

Xie, M., & Baumer, E. P. (2019). Neighborhood immigrant concentration and violent crime reporting to the police: A multilevel analysis of data from the National Crime Victimization Survey*. *Criminology*, *57*(2), 237–267. https://doi.org/10.1111/1745-9125.12204

Xie, M., & Baumer, E. P. (2021). Immigrant status, citizenship, and victimization risk in the United States: New findings from the National Crime Victimization Survey (NCVS)*. *Criminology*, *59*(4), 610–644. https://doi.org/10.1111/1745-9125.12278

Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis. *Journal of Consumer Research*, *37*(2), 197–206. https://doi.org/10.1086/651257

Zhou, M. (1995). *Chinatown: The socioeconomic potential of an urban enclave* (Vol. 43). Temple University Press.

Zhou, M. (2013). 5. Chinese: Diverse Origins and Destinies. In *One out of three: Immigrant New York in the twenty-first century*. Columbia University Press.

Zill, N. (2016). Most immigrant families are traditional families. *Institute for Family Studies*, *11*, 30.

Zimring, F. E. (2008). *The Great American Crime Decline*. Oxford University Press.