ABSTRACT

Title of Dissertation:	A SPATIOTEMPORAL ANALYSIS OF COLLECTIVE HUMAN MOBILITY PATTERNS AND CRIME VARIATIONS IN BALTIMORE CITY
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Researchers have examined the patterns of peoples' spatiotemporal movements to understand various aspects of our society, including urban crime risks. While prior research has extensively explored individual mobility, collective mobility patterns have received relatively little attention. The growing availability of mobile device location data offers new opportunities to analyze those collective patterns, which used to be challenging to capture. Traditionally, residential mobility and inward flow have been used to study collective mobility, but other measures—such as outward flow—have often been overlooked. Beyond the primary relationship, the spatial distribution of local security measures, such as the intensity of police patrols, may further influence this connection. Temporal variations in the mobility-crime relationship may also arise due to factors like seasonal temperature changes, shifting

activity preferences, uneven distribution of holidays, and differences in traveler composition across days of the week.

This study explores the relationship between collective human mobility patterns and crime victimization in Baltimore City. It also examines how mobility-crime connections vary across different neighborhoods with intense police activities and during different periods. Using a comprehensive dataset that integrates mobile device location data, official crime reports, and community-level information, the study examines three crime types: homicide, robbery, and burglary. The primary mobility indicators include residential mobility, inward population flow, and outward population flow. Poisson regression with Moran Eigenvector Spatial Filtering (MESF), controlling for ambient population as an exposure variable, is used for the analysis.

Key findings include: (1) higher volumes of inward and outward population flows are consistently associated with lower robbery and burglary rates, while residential mobility is positively associated with burglary rates; (2) neighborhoods with more intense police activity exhibit a stronger positive link between mobility and crime; and (3) both seasonal and intra-week (weekday vs. weekend) variations exist in the mobility-crime relationship, though clear seasonal patterns are lacking. Weekday-weekend differences are particularly notable for inward population flow. Those results highlight the importance of collective mobility in shaping local crime risks and call for deeper investigation into the nuanced dynamics between collective mobility and urban safety.

A SPATIOTEMPORAL ANALYSIS OF COLLECTIVE HUMAN MOBILITY PATTERNS AND CRIME VARIATIONS IN BALTIMORE CITY

by

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Dissertation submitted to the Faculty of the Graduate School of the University of Maryland, College Park, in partial fulfillment of the requirements for the degree of Doctor of Philosophy
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Dedication

To my parents, whose love and sacrifices have been the bedrock of my journey.

And especially to my father—

for the dream you carried in your heart,

the one you passed on to me.

Though life has placed different paths before you,

your passion for learning and research shines through in this work.

This dissertation is as much yours as it is mine.

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Chapter 1: Introduction

Human mobility, or the movement of people across space and time, is an essential characteristic of human behavior (Zhao et al., 2021). Researchers use recurring elements of daily trajectories in people's movements, known as mobility patterns, to recognize and forecast individual lifestyle and population behavioral changes within society (Ben Zion & Lerner, 2018). Human mobility patterns can be divided into two categories: individual and collective. Individual mobility research studies the resources everyone can access, and the resulting trips based on their activities (González et al., 2008). Collective human mobility research instead focuses on the large-scale, aggregated trips of the population across areas and networks (Peng et al., 2012). Understanding the spatiotemporal patterns of human mobility during people's daily routines has proven helpful in traffic safety control (H. Zhang et al., 2022; J. Zhang et al., 2021), urban governance (Noulas et al., 2012), public health enhancement (Kraemer et al., 2020), and pollution treatment (Benita, 2021). Moreover, after being recognized for its great potential, human mobility research has also gradually extended into the field of criminology.

Criminological researchers have consistently aimed to discover critical elements affecting fluctuations in crime rates and the probability of urban victimization, providing essential guidance for policy implementation. The potential criminal risk associated with changes in population distribution within urban areas is an appealing theme (Andresen, 2011; S. D. Johnson & Summers, 2015). In urban environments, the population consists of both permanent residents and temporary visitors. The movement of people within and between different locations leads to a variation in population density (Boivin & D'Elia, 2017; Felson & Boivin, 2015). Therefore, the investigation of population movement patterns, often known as "*collective mobility patterns*," has increasingly become an important criminological focus. Moreover, as demonstrated throughout this study, analyzing human mobility patterns can enhance our understanding of how criminal behavior and victimization are distributed across time and space.

Statement of the problem

Although human mobility patterns have received much attention in prior criminological theories, the empirical work on this theme has been far from conclusive (Byrnes et al., 2017; Felson & Boivin, 2015; Kadar et al., 2015; Sugie & Lens, 2017). Previous studies regarding the role of collective human mobility patterns on crime outcomes have several shortcomings.

First, many extant studies have focused on individual human movement patterns, which are usually less time-consuming and less expensive to capture and measure than collective human movement patterns (Bernasco & Nieuwbeerta, 2005; S. D. Johnson & Summers, 2015; Tseloni et al., 2004). These studies often ignore trends or variations encoded in collective human mobility patterns that are not detectable once broken down into individual movements (Browning et al., 2021). The variations in collective human mobility patterns differ from the sum of everyone's separate movement patterns within a given population.

Second, the dynamic feature of collective human mobility requires appropriate data sources to measure and demonstrate its contributions (Browning et al., 2021; Cagney et al., 2020). Nevertheless, most previous studies have included proxy measures to account for spatial mobility patterns or only captured a limited proportion of mobility flows (Agnew, 2020; Kadar et al., 2015; N. Li & Kim, 2023; McCutcheon et al., 2016). Previous research on dynamic population flows has also predominantly examined inward movements, focusing on the number of people entering a specific neighborhood as their destination (Felka et al., 2020; G. Song et al., 2019). In contrast, other forms of population movement—such as outward flows (i.e., the number of people leaving a location), transit flows through particular areas, and the balance between inward and outward flows across different locations—have received comparatively little attention in the literature (Summers & Johnson, 2017). Few studies have examined collective human mobility patterns beyond a single neighborhood, taken different measures into account, and applied innovative data sources to capture mobility flows within a broad ecological network (Hipp & Kim, 2019; McCormick et al., 2017; Saxon, 2021; G. Song et al., 2023).

Third, the distribution of locations with intense police activities and high crime concentrations can complicate the relationship between human mobility and crime (Lum et al., 2022; Nix et al., 2021). Sherman and colleagues (1989) defined those crime concentration areas as "hot spots," indicating a complex neighborhood crime history, enhanced police patrols, and other strategies applied to those areas. As hot spots and other areas can have different environmental features and security measures, it is possible that the range of hot spots and intensity of police activities within neighborhoods can affect the relationship between human mobility and crime, a possibility that has not been considered in prior work (P. J. Brantingham et al., 2020; G. Song et al., 2019). Further, given the potential differential movement patterns among hot spots and other areas, information regarding human movement patterns also has the potential to help understand why crimes occur, inform criminological theories, and promote police effectiveness (Hibdon et al., 2021; Hibdon & Groff, 2014).

Finally, intraday, intraweek, and seasonal fluctuations may be present in the relationship between human mobility and crime (Haberman et al., 2018; W. D. Lee et al., 2021; G. Song et al., 2023). Recognizing that mobility and crime are dynamic, scholars keep exploring the underlying mechanisms contributing to their temporal fluctuations (J. P. Lynch & Addington, 2006; Mahfoud et al., 2021; Towers et al., 2018; Tucker et al., 2021). Analyzing their temporal variations is thus necessary to comprehensively examine the mobility-crime connection (Andresen & Malleson, 2015; de Melo et al., 2018; Nouvellet et al., 2021). Still, most studies of crime periodicity ignore collective human mobility as a potential mechanism for temporal changes in crime rates.

Current research aims

The current study responds to these limitations in past research in several ways. First, I measure human movement patterns more directly and precisely than most prior research on mobility by using cellphone users' signal trajectories as a data source. Second, I provide evidence to support policies for better policing strategies by recognizing the differential relationship between human mobility and crimes across areas with various intensities of police patrol activities. Third, by examining the whole year of 2019 and considering variations in human movement patterns, I offer a more detailed and comprehensive picture than extant studies about how mobility-crime connections vary across different days, weeks, and months within a year.

The current study concentrates on Baltimore City, the largest city in Maryland. I generate a dataset based on multiple data sources to assess whether collective human movement patterns, represented by residential mobility and dynamic mobility flows, can predict the occurrence of crime incidents. I examine whether the intensity of police patrol activities, with the coverage of police-generated crime hotspots as the proxy, strengthens the relationship between human mobility and crime. Through longitudinal analyses, I also examine how the relationship between collective mobility patterns and crime rates may change over time, varying between weekdays and weekends and across seasons of the year. My main objectives are to conduct a comprehensive and precise analysis of the proposed relationship between mobility and crime, provide valuable perspectives for hotspot policing strategies, and offer concrete recommendations for the prevention and reduction of crime.

<u>Outline of the dissertation</u>

In the current chapter, I discuss collective human mobility patterns and crime, summarize the gaps in prior research, preview the research questions, and list some potential contributions of this dissertation. In Chapter 2, I summarize the theoretical perspectives on the relationship between human mobility and crime. In Chapter 3, I review: 1) research on the essential relationship between human mobility and crime opportunities, 2) the potential variance of mobility-crime connections due to various coverage of police patrol activities in neighborhoods, and 3) the role of human mobility in the fluctuation of crime incidents over time. At the end of each subsection, I introduce research questions and list potential hypotheses to be tested.

In Chapter 4, I describe details regarding the data, measures, and analytic strategies. To balance the feasibility of data acquisition and the appropriateness of the unit of analysis, I treat census tracts as neighborhoods and draw on different data sources to construct the dataset, capturing information on crime, human mobility, community characteristics, and land use information in Baltimore between 2014 and 2019. I use the Poisson regression with Moran Eigenvector Spatial Filtering (MESF) as the model for the primary analyses. I also provide a variety of robustness tests and sensitivity analyses.

In Chapters 5 through 7, I present the detailed analytic results corresponding to each research question. In Chapter 5, I present the descriptive analysis and examine both unadjusted and adjusted mobility-crime relationships in regression models. In Chapter 6, I use Poisson regression with MESF models to explore the moderating role of police patrol activity on the relationship between mobility and crime. In Chapter 7, I present panel analysis results using weekly and daily counts of crime incidents as the outcome and explore the temporal variation within the mobility-crime relationship through four seasons of the year and across weekdays and weekends.

In Chapter 8, I summarize major findings and connect the results to prior studies and the theoretical conceptualization. I review the theoretical and empirical contributions as well as policy implications in this chapter. I also provide limitations of the study and suggestions for future research.

Chapter 2: Theoretical Background

The phenomenon of human mobility, involving the spatial and temporal movement of individuals and groups, constitutes a fundamental aspect of human behavior (Zhao et al., 2021). Human beings are inherently mobile, manifesting both individually, in the forms of commuters and tourists, and collectively, as seen in gatherings and crowds (Cresswell, 2011). For many years, researchers have examined mobility patterns to gain insights into individual lifestyles and broader societal trends (Ben Zion & Lerner, 2018). Collective human mobility patterns emphasize aggregate-level population movements within networks and across various areas (Peng et al., 2012). The involvement of both residents and visitors in population movements contributes to the complex nature of collective mobility. Those patterns also emerge as multifarious products of the interaction between diffusive and directed population movements (González et al., 2008; Padgham, 2012).

In this chapter, I review criminological perspectives on the mobility-crime relationship. In the first section, I focus on the social disorganization theory and the broken window thesis, discussing the potential role of residential mobility in forming an environment conducive to neighborhood crimes. In the second section, I concentrate on the situational opportunity perspectives, especially the routine activities theory and the crime pattern theory. I discuss how dynamic population flow functions as a driving force to influence crime rates and the distribution of crime opportunities in urban spaces.

Collective mobility as (neighborhood) residential mobility

Collective patterns of human mobility represent aggregated spatiotemporal movements of populations or groups, capturing *how people collectively travel, commute, migrate, or move* *within or between geographic locations over various periods*. As collective patterns of human mobility involve different forms of aggregated spatial and temporal movements, researchers commonly distinguish between two distinct but complementary dimensions: 1) residential mobility/turnover, 2) dynamic population flow/movement. The first dimension, residential turnover, primarily captures *the number of residents moving into, out of, or within communities over extended periods, thus reflecting the migration and relocation patterns associated with changing residential locations* (Shaw & McKay, 1942). In contrast, the second dimension, dynamic population movement, represents *the continuous or regular movement of people into, out of, or through geographic areas, mostly driven by daily activities, such as business/working, commuting, education, shopping, or leisure/recreation* (Cohen & Felson, 1979). Because dynamic population flows capture relatively rapid, short-term movements tied to daily or frequent activities, they complement the slower, longer-term movements associated with residential relocations and shifts in neighborhood residential composition reflected by residential turnover. While these two dimensions represent distinct temporal and spatial scales of collective mobility, together they offer a comprehensive understanding of how people interact with urban environments—through both long-term residential relocations and routine, everyday movements.

Almost a century ago, the Chicago School of Sociology began to study how spatial collective movements can affect the distribution of crime risks. Park and Burgess (1925) have observed that urban resource competition divides cities into concentric zones, with proximity to the city center shaping neighborhood development. As urban populations grow, individuals migrate from inner-city areas to suburbs, resulting in affluent neighborhoods on the city's outskirts. Conversely, the central "transition zone" experiences social and physical decay, becoming a hub for social disorganization and crime (Inlow, 2021). This gradual migration process from one area to another roughly reflects the movement patterns of early urban residents. The early theorists of the Chicago School not only presented the impact of the residential movement and group concentration on urban social structure and crime but also provided a basis for subsequent theoretical development (Park & Burgess, 1925).

The socio-spatial analysis of crime has become increasingly popular under the influence of the Chicago School, and one of its major models is social disorganization theory. The social disorganization theory formally raises the concept of residential mobility (turnover), which refers to how frequently residents switch homes, change their households/addresses, and move within, into, or out of areas (Shaw & McKay, 1942). Shaw and McKay (1942) define social disorganization as *a community's inability to uphold the shared values of its residents and to exercise adequate social control*. According to Shaw and McKay (1942), social disorganization serves as a key driver of crime, emerging from specific structural conditions within communities. Communities characterized by high residential turnover, population heterogeneity, and poverty face heightened social disorganization, exacerbated by urbanization and governance challenges (Sampson & Groves, 1989; Shaw & McKay, 1942). When neighborhood residents mutually trust and support each other, social cohesion is strong (Sampson et al., 1997). Sampson and colleagues (1997) argue that social cohesion enables residents' collective willingness to intervene for informal social control enforcement within neighborhoods. High residential turnover disrupts local friendships and organizational connections, which are crucial for effective social control (Bursik & Grasmick, 1993). Besides close friendships among neighbors, stable, long-term residency and residents' interactions through parks and other public areas also promote social cohesion. The converse is also true: areas with high levels of residential mobility have weak social cohesion, leading to a lack of social control, and high crime rates (Messner, 1986; Messner

& Blau, 1987; Sampson et al., 1997). As a result, these compromised networks diminish effective resident communication, impede neighborhood interaction, and foster environments conducive to crime (Sampson & Groves, 1989).

Another perspective that incorporates residential mobility into its framework, apart from social disorganization theory, is the broken windows thesis. Unlike social disorganization theory, which suggests that residential mobility directly leads to social disorganization and subsequently influences crime rates, the broken windows thesis argues that the tolerance of neighborhood disorders drives residents to move away, ultimately contributing to an increase in crime. Although social disorganization theory discusses neighborhood disorders, it primarily views them as both a consequence and a reinforcing factor of significant disadvantage and weakened social bonds within a community, ultimately contributing to higher crime rates (Sampson & Raudenbush, 1999). The broken windows thesis, developed by Wilson and Kelling (1982), offers a different perspective by clarifying the relationship between disorder and crime and bringing it to public attention. Wilson and Kelling (1982) argue that untreated disorders send a signal that "no one cares," which both attracts criminals and discourages residents from remaining actively engaged in their neighborhoods. Both physical (e.g., graffiti) and social disorder (e.g., public drunkenness) can increase residents' fear, encourage them to move, and reduce the level of informal social control--leading to more criminal activities (Hinkle & Weisburd, 2008).

From simple disorder to serious urban decay, such a process can be viewed as a gradual human movement activity: residents become fearful of crimes as they discover that disorders are not being appropriately treated in their neighborhoods (Sampson & Raudenbush, 1999). Residents also find it hard to maintain order, establish informal control mechanisms, and gradually withdraw from their neighborhoods due to the increased risk of victimization

(Weisburd et al., 2015). During this process, potential offenders recognize the low level of informal social control and perceive neighborhoods as welcoming their presence without challenges (Bratton & Kelling, 2015). For example, a high volume of vacant housing, through substantial population loss over the years, can encourage potential offenders to mark those neighborhoods as suitable for criminal activities (Jones & Pridemore, 2016). Visible housing vacancy, accompanying the neighborhood's population loss, reduces guardianship, increasing criminal opportunities. Such circumstances attract criminals (Branas et al., 2012; Porter et al., 2019). The low average value of neighborhood housing can be another sign of community decay, since the low housing price demonstrates people's lack of faith in neighborhood stability, which is further linked to underlying security concerns (Accordino & Johnson, 2000; Immergluck & Smith, 2006). Therefore, the appearance of neighborhood-related physical and social disorders initiates the process of residential mobility and population loss and ultimately leads to increasing crime.

Both social disorganization theory and the broken windows thesis incorporate residential mobility as a key aspect of neighborhood crime rates. Although each framework emphasizes residential mobility at different stages of development, both recognize it as a significant factor contributing to variations in neighborhood crime rates (Chappell et al., 2011; O'Brien & Sampson, 2015; Skogan, 2015; B. C. Welsh et al., 2015). They also both argue that residential mobility is a long and gradual process, as residents typically remain in a location for months, years, or even decades before deciding to move to a different address. However, as I will show in the next section, residential mobility is only part of the story when it comes to collective movement patterns. Under certain circumstances, changes in mobility patterns may also be rapid.

Collective mobility as dynamic population movements

Since the 1960s, the rise of situational opportunity perspectives, or more broadly, environmental criminology, has dramatically changed the conceptualization of collective mobility. Environmental criminologists examine how the physical and social environments where individuals live influence their criminal behavior and victimization (P. Brantingham & Brantingham, 1995). For example, Crime Prevention Through Environmental Design (CPTED) proposes that geographical features of the built environment influence how individuals move within and through neighborhoods, and the likelihood of potential offenders targeting individuals or properties within neighborhoods (Inlow, 2021; Roncek, 1981). Therefore, environmental criminologists consider collective mobility not merely as a neighborhood characteristic but as an essential factor that connects building design, neighborhood layout, and other features (P. L. Brantingham & Brantingham, 1993; Cohen & Felson, 1979; Hindelang et al., 1978). Together, these elements create potential opportunities that may lead to criminal activities (Anderson & Hodgkinson, 2021).

Environmental criminologists have expanded the concept of collective mobility beyond residential mobility. For example, routine activities theory (RAT) not only examines how environmental features interact with human activities to create crime opportunities, but also acknowledges the movement of visitors as part of collective mobility (Cohen & Felson, 1979). Cohen and Felson (1979) argue that people travel to work, school, recreation, and home on a daily basis, which provides opportunities for potential offenders and victims to come into contact. Therefore, for a specific neighborhood or location, the daily population present should include not only residents who remain in the area, but also residents who travel out of the area and visitors from other neighborhoods. The routine activities approach posits that criminal opportunities arise when three critical components converge during daily activities: 1) the presence of motivated perpetrators, 2) the existence of suitable targets for targeting, and 3) when capable guardians are absent (Cohen & Felson, 1979). More importantly, routine activities theory (RAT) recognizes that potential perpetrators, victims/targets, and guardians are not limited to residents but also include visitors who do not permanently reside in the area. Within this variable population, various indoor and outdoor risky activities or lifestyles, combined with everyday collective movement within and between areas, affect individuals' and properties' exposure and proximity to potential offenders. These factors enhance their accessibility and attractiveness, ultimately contributing to victimization when guardianship is absent or inadequate (Birkbeck & LaFree, 1993; Cohen et al., 1981; Hindelang et al., 1978). From a macro-level perspective, the RAT provides a theoretical foundation for the impact of the collective movement of both residents and visitors on criminal opportunities (Averdijk et al., 2016; Felson & Cohen, 1980; Roncek & Maier, 1991).

Subsequent theoretical advancements connect collective mobility to the spatiotemporal analysis of crime patterns by exploring its role in creating overlap between individuals’ activities and the spaces they occupy (Sidebottom & Wortley, 2015). Brantingham and Brantingham (1981) bring in the "geometry of crime" to link the locations of routine activities and the routes connecting them to criminal activities. They argue that, influenced by their surrounding environment, individuals visit various activity locations or nodes—such as their workplace, school, gym, and others—during their daily routines ((P. L. Brantingham & Brantingham, 1993, 2008)). Moreover, their movement activities require the awareness and utilization of paths to connect those activity nodes (P. J. Brantingham & Brantingham, 2016). Many of these activities become nearly impossible without the pathways to connect different physical venues where people interact. People create or maintain their activity routes through different mobility modes, such as airplanes, trains, private vehicles, bicycles, or walking. Therefore, each individual's activity space comprises a network of activity nodes and the routes or pathways that link them together. Additionally, the patterns of mobility and variations in the daily population size influence the geographical preferences of prospective offenders. Individual criminals often follow the same pathways as the broader population (Boivin & Felson, 2018). They are attracted to areas frequently visited by others, which increases the likelihood that their movement paths will intersect with those of potential targets (Menting et al., 2020). The similarities in daily routines and movement patterns of both offenders and the general population result in overlapping activity spaces. This spatiotemporal convergence, where the movements of offenders and targets intersect, contributes to the clustering of criminal incidents around specific locations and pathways (P. Brantingham & Brantingham, 1995). In this sense, the social interaction within individual activity spaces constitutes a necessary part of daily life and illustrates the complexity of human activities.

Crime pattern theory further differentiates how collective mobility transforms certain locations into target-rich crime generators or attractors for specific offenses. Brantingham and Brantingham (1981; 1993) argue that the urban structure is shaped by areas with different land uses and road networks, which influence where activity locations are created and where crime concentrations are more or less likely to occur. Some places that attract high volumes of people may become crime generators. For example, public transportation hubs and train stations have been linked to property offenses, such as burglary (Kadar et al., 2015). On the other hand, places like bars and nightclubs can become crime attractors, drawing large numbers of strangers into a confined space within a short period, creating many opportunities for crime (P. Brantingham &

Brantingham, 1995). It is important to note that it is not the categories of facilities or land uses themselves that appear to influence variations in crime, but rather the high quantity of traffic or mobility flows associated with those types of land uses or facilities (Wilcox & Cullen, 2018; Wilcox & Eck, 2011). Therefore, collective mobility shapes the size and composition of the population, as well as the availability of attractive targets, both of which contribute to crime opportunities (Cagney et al., 2020).

The impact of dynamic population movement on neighborhood safety can be a double-edged sword: While daily inflows and outflows may expose communities to increased security risks, such mobility can also create conditions that reduce opportunities for crime. On the one hand, dynamic population movements—through the influx of visitors and the departure of residents—can increase the likelihood of convergence between potential offenders and suitable targets when capable guardians are absent (Cohen & Felson, 1979). The dynamic and complex nature of inward and outward population flows creates conditions where potential offenders can easily locate and approach victims, get close to them, commit crimes, and escape (J. Katz, 1988; B. Miller & Ponto, 2016). Offenders can move between communities or regions for opportunities (Liu et al., 2022), and quickly flee to distant areas to evade capture (Van Koppen & Jansen, 1998). High flows of people and vehicles also complicate crime prevention and tracking efforts by authorities (Sampson & Wooldredge, 1987). The increased number of visitors can weaken the deterrent effect of local police presence, while prevalent outward activity reduces the overall level of guardianship. Together, these dynamics heighten the challenges residents and law enforcement face in distinguishing between locals, newcomers, and transient populations.

On the other hand, active inward and outward population movements can also produce beneficial effects for neighborhood safety. High levels of inward mobility may enhance informal surveillance by increasing the number of "eyes on the street" and introducing additional individuals who can act as potential guardians (Cohen & Felson, 1979; Jacobs, 1961). This means a higher likelihood that someone will witness, report, and even intervene with suspicious behaviors. At the same time, outward flows may reduce crime opportunities by reducing the number of available offenders and targets within neighborhoods (Felson & Cohen, 1980). Increased interaction among residents and visitors can also strengthen social bonds, trust, and responsibility, all of which can increase informal social control. Outward population movement can also enhance the active participation of those left in the neighborhood. The remaining residents may form informal support networks and become actively engaged in local initiatives (e.g., local events, neighborhood associations), strengthening their civic life. In addition, the coexistence of substantial inward and outward mobility can motivate law enforcement to increase their presence or invest in crime prevention measures, such as more patrols or CCTV cameras (Piza et al., 2019), deterring potential criminals through the presence of capable guardians. These actions not only serve as a deterrent to crime but also encourage both residents and temporary visitors to engage with law enforcement and utilize existing safety resources—ultimately contributing to improved neighborhood security.

The adaptation of routine activities theory, along with the development of the geometry of crime and crime pattern theory, underscores the critical role that movements of both residential and nonresidential visitor populations play in shaping neighborhood crime patterns. The dynamics of those collective movements influence the accessibility of potential offenders, targets, and guardianship measures, thereby altering the distribution of criminal opportunities (Andresen, 2010). Further, the situational opportunity perspective views collective mobility as a dynamic process, considering both the rapid emergence of residents from their living spaces and the significant influx of visitors converging in specific areas within a short time frame. In addition, the time units for empirical studies based on this approach can be as small as weeks, days, or even hours. Moreover, directionality becomes essential for understanding dynamic population flows, as it reveals the origins and destinations of movement across various locations and aids in measuring the potential trajectories of populations passing through different neighborhoods. As a result, directional and dynamic population flows are no longer static; instead, they have become crucial variables influencing urban safety and quality of daily life.

Summary: connecting collective mobility patterns to crimes

Historical neighborhood approaches and contemporary situational opportunity perspectives have both established theoretical links between collective patterns of mobility and crime victimization despite significant differences in specific concepts. They both propose that crime is correlated with the population movement patterns in a particular area, either due to residents' relocation or the dynamic movements of daily visitors (Boivin & Felson, 2018). Based on this logic, understanding collective movement patterns may help identify the specific areas where criminal activity is most likely to occur and changes in overall crime rates.

Criminological theories have demonstrated that patterns of human movement play a role in crime victimization in urban areas. However, much of the existing research analyzes residential mobility or the dynamic movement of populations separately, rather than viewing them as part of the sizeable collective mobility system. This distinction matters because residential mobility influences how far people, including potential offenders, travel (Ackerman & Rossmo, 2015), and taking dynamic population flow into account can change how residential mobility relates to crime rates (Stults & Hasbrouck, 2015). Understanding how mobility patterns impact crime victimization requires examining both factors together. In addition to the primary mobility-crime connections, it is essential to understand the spatial variations within this relationship, as they can guide empirical research and inform policy recommendations in criminal justice practice. Furthermore, a spatiotemporal analysis of human mobility and crime would be incomplete without considering the temporal dimension of this relationship. Therefore, in the next chapter, I discuss the empirical evidence regarding the primary mobility-crime connection and the potential spatial and temporal variations within this relationship.

Chapter 3: Empirical Background

In this chapter, I review empirical studies on the mobility-crime relationship across three key dimensions. The first section explores the link between collective mobility patterns and crime, summarizing research on residential mobility and dynamic population flows. The second section examines potential spatial variations in this relationship, highlighting police patrol activities as a possible source of these variations. The third section discusses temporal variations in mobility and crime, such as seasonal effects and weekday/weekend variations. At the end of each section, I pose the relevant research questions and outline hypotheses to be tested in the latter half of this study.

Primary connections between mobility and crime

I. Residential mobility/turnover

The social disorganization perspective suggests that high residential mobility is one observable characteristic of communities that can attract potential criminal activities (Shaw & McKay, 1942). Existing studies have investigated its correlation with crime victimization across various contexts (Bernasco & Luykx, 2003; Boggess & Hipp, 2010; J. M. MacDonald & Stokes, 2020; Peeters et al., 2018). In general, most studies using cross-sectional datasets have confirmed the existence of a significant link between residential mobility and neighborhood crimes, with variations due to measurement selection, neighborhood settings, and crime types (Peterson & Krivo, 2010; Sampson et al., 1997; Van Wilsem et al., 2006; Xie & McDowall, 2008). For example, Boggess and Hipp (2010) discover that the notable influence of residential mobility on violent crime becomes apparent only when employing the general residential turnover index, which involves the residential mobility of both homeowners and renters, rather than when homeowner stability is considered or measured independently. Also, Shihadeh and Barranco (2010) observe that residential instability in Latino communities is associated with the strengthening of group bonds and community cooperation to embrace newcomers, consequently leading to a decrease in community violence. However, this reduction effect is absent in black-majority communities (Shihadeh & Barranco, 2010). Moreover, although earlier research frequently links rising crime rates to the breakdown of community ties resulting from residential turnover, accounting for the spatial effects of gentrification in the model reveals that homeowner mobility may, in fact, be associated with decreases in aggravated assaults and robberies (Boggess & Hipp, 2016). And the heightened degree of residential instability can also contribute to decreased property crime incidents (Hipp & Luo, 2022).

In longitudinal or panel studies, previous research has produced mixed findings regarding the relationship between residential mobility and crime victimization (Braakmann, 2023; Hipp, 2010; Hipp et al., 2009). Hipp and his colleagues (2009) have found that while high residential mobility has little impact on violent or property crime levels in subsequent years, the negative impact of crime rates on home sales and property values is significantly more pronounced. Later, Hipp (2010) has further found no evidence that residential inability is substantially linked to the rise in crime rates a decade later. Several additional studies have echoed these findings (Boggess et al., 2013; Hipp & Wickes, 2017), although some maintain that despite its minor impact, higher residential turnover can still contribute to elevated overall crime rates (Braakmann, 2023; Hipp & Chamberlain, 2023).

Building on the broken windows thesis, previous studies have also highlighted the crucial role of residential mobility in the strong link between neighborhood disorder and crime (Kirk & Hyra, 2012; B. C. Welsh et al., 2015). Jones and Pridemore (2016) argue that burglary incidents increase in areas with high housing vacancy rates. This is because population loss—resulting from residents moving out—leads to diminished guardianship, making neighborhoods attractive targets for burglars. Furthermore, there are valuable materials often left within those vacant homes that can be easily stolen and sold for money (Jones & Pridemore, 2016). Ellen and colleagues (2013) and Cui and Walsh (2015) have found that when homes are foreclosed and predominantly purchased by banks, residents are forced to leave the neighborhood. This displacement results in long-term vacancies across multiple units, which is directly associated with an increase in reported violent crimes (Cui & Walsh, 2015; Ellen et al., 2013; Lacoe & Ellen, 2015). Other studies have also found a strong link between housing vacancies and both violent and property crimes, noting that residents leaving the area and the associated population loss plays an important role (Branas et al., 2012; Chen & Rafail, 2020; Immergluck & Smith, 2006; Porter et al., 2019). However, research on drug-related crimes has shown mixed results, with studies disagreeing on how much drug use and drug dealing occur at vacant properties when residents move out (Accordino & Johnson, 2000; Chen & Rafail, 2020; DeLuca et al., 2019; R. Taylor, 2018).

II. Dynamic population flow

Compared to the extensively studied long-term residential mobility, measuring short-term, directional, and dynamic population flow is not an easy task. First, dynamic population flow is more than just aggregating individual movement trajectories. Human mobility patterns can be scale-dependent, and the trends or variations in dynamic population flows may be obscured when broken down into individual movements (Alessandretti et al., 2020; Brockmann et al., 2006). However, aggregating mobility trajectories often results in the loss of population heterogeneity in travel patterns and demographic details of the travelers. Still, treating dynamic population flows as the sum of individual movements ignores the social interactions and interconnected impacts among travelers, which are essential for crowd formation and the development of collective behavior (Brockmann et al., 2006; Guo et al., 2022; C. Song et al., 2010).

Second, many extant studies have used neighborhood accessibility, land use, and other measures, which cannot directly measure this dynamic feature. Some studies concentrate on how community accessibility of mobility flows affects neighborhood crime levels (Vandeviver et al., 2019; Ward et al., 2014). These studies have found a positive link between accessibility and neighborhood crimes, such as burglaries (Bernasco & Luykx, 2003; Sohn et al., 2018; Vandeviver et al., 2019). Increased accessibility, bringing people and vehicles into and through areas, can lead to higher crime levels (Saghapour & Moridpour, 2019; Tillyer & Walter, 2019a). Tillyer and Walter (2019) also note that low crime levels are observed in some low-income housing projects when strong security and design features are used to regulate entry, monitor activities, and raise the costs of offending. Other studies examine how land use patterns influence neighborhood crime variation. Non-residential land uses, like bars or fast-food restaurants, are often linked to increased criminal opportunities (Bernasco & Block, 2011; Pridemore & Grubesic, 2013; Tillyer & Walter, 2019b). High-density residential and commercial areas are associated with higher violent crime rates ((Stucky & Ottensmann, 2009), while Browning et al. (2010) find a nonlinear link between neighborhood density and violent crime. Sampson and Raudenbush (1999) find no strong link between mixed land use and crime, whereas Andresen et al. (2011) report that mixed-use areas experience lower crime rates compared to areas designated only for commercial use.

In addition to neighborhood accessibility and land use patterns, some studies use other proxy measures to capture aspects of dynamic population movement. For example, Agnew (2020) links the expansion of motorways to the increase in burglary incidents. McCutcheon and colleagues (2016) find that more interstate access, represented by the number of highway and freeway exits, can contribute significantly to the increase in robbery incidents in Georgia. The main issue with this approach is that the flow of people between different locations within the mobility network is constantly changing (Leng et al., 2021; Noulas et al., 2012). Measures like neighborhood accessibility or the percentage of mixed land use, which remain constant over specific periods, only reflect factors that influence movement patterns, not the actual dynamics of collective human mobility (Boggess & Hipp, 2016; Jones & Pridemore, 2016). Those characteristics can even interact with collective human movements to create differential criminal opportunities (N. Li & Kim, 2023; Liao et al., 2019).

Third, individuals and places are not isolated but embedded in systems of location interconnectivity based on dynamic population movements. Networks of people are linked via shared routines, and places are connected through mobility flows. This underscores the need for appropriate data collection and measurement strategies to operationalize the ecological network of dynamic population flows and demonstrate its effect on crime (Browning et al., 2021). Based on this reasoning, multiple studies have begun to investigate dynamic population movements by leveraging new data sources, such as travel surveys, public transportation ridership, and geo-coded Twitter data (Boivin & Felson, 2018; Gerell, 2021; W. D. Lee et al., 2021; G. Song et al., 2018; Stults & Hasbrouck, 2015; Tucker et al., 2021; Wo et al., 2022). Other scholars use commuting data: Li and Kim (2022) include the annual number of subway riders as the predictor for various crime types in New York City but only find positive effects on burglary and robbery incidents. Hipp and Kim (2019) use similar sources from Southern California to explore the link between mobility flows and crime at the street-segment level, discovering that robberies are more likely to occur in segments with fewer regular employees. Through the integration of census data with household transportation surveys, Boivin and Felson (2018) uncover a connection between an increase in incoming visitor flows and a higher incidence of visitors facing charges for crimes, as well as an increase in the number of local residents facing criminal charges. These effects are notably heightened in areas where the primary purpose of visits is leisure activities (Boivin & Felson, 2018). Song and colleagues (2018) discover that during specific periods, taxi ridership is an effective indicator to gauge the population at risk for crime victimization because it provides a relatively precise representation of outdoor activities, in contrast to indoor activities. Using Twitter data, Hipp and colleagues (2019) demonstrate that temporal fluctuations in ambient populations are key to understanding South California's block-level crime patterns across various periods (Hipp et al., 2019). Although these studies greatly improve on previous spatial crime studies, the variations in data quality, user coverage, and measurement accuracy remain a huge challenge (Browning et al., 2021).

More recently, the introduction of geographically referenced cellphone data presented researchers with promising opportunities for examining dynamic population movements during daily routines (Haleem et al., 2021; G. Song et al., 2022, 2023). Compared to other sources, geo-referenced cellphone data has more extensive population coverage and higher predictability of human behavior (P. Johnson et al., 2021; Lu et al., 2013; Zhao et al., 2021). Song and colleagues (2019) utilize GPS data and find that the level of connectivity between the neighborhood of a convicted offender and the neighborhood that the offender targets as the destination, as indicated by collective mobility patterns, correlates with the offender's likelihood of committing crimes in that destination neighborhood. Felka and colleagues (2020) affirm a statistically significant yet complicated association between the concentration of mobile phone users and crime. The complexity of this connection arises from factors such as the specific area examined and the type of crime (Felka et al., 2020). Likewise, Johnson and colleagues (2021) identify variations in the spatial distribution of rates for various types of property crimes by employing cell tower location data. They utilize the number of cell phone users as an estimation for the ambient population, contrasting it with the residential population as the conventional measure of the population at risk (P. Johnson et al., 2021). Integrating geo-referenced cellphone data with machine learning techniques has become valuable in predicting both short-term and long-term crime rates and hotspots, thereby reinforcing its appeal as a source for investigating the relationship between mobility and crime (Caminha et al., 2017; Kadar & Pletikosa, 2018; Wu et al., 2022).

Overall, accurately tracking collective human mobility patterns used to be a significant challenge in criminology. With technological advancements, especially the rise of mobile device location data during recent years, measuring dynamic population movement—once difficult to capture—has been dramatically transformed. Still, challenges persist in some areas, such as the transportation modes involved and the detailed movement trajectories of pedestrians, non-motor vehicles, and motor vehicles in specific locations, which are often unknown or undisclosed (Bernasco, 2010; Gallison & Andresen, 2017). Additionally, prior studies that consider the direction and type of dynamic population flows have primarily focused on inward flows, or the volume of population entering a specific neighborhood as the destination (Felka et al., 2020; G. Song et al., 2019). Other types of population flows, such as outward flow (i.e., the volume of population leaving a location), the flow of people passing through certain areas, or the ratio of inward to outward population flows between different locations, are largely absent in existing research (Ward et al., 2014). Researchers should continue exploring various indicators of dynamic population movement, further examining the links between collective mobility patterns and neighborhood crimes, and recognizing collective mobility patterns as an essential aspect of urban life.

III. Exploring the mobility-crime connections

Whether using proxy or direct measures, most previous studies have shown that intra-area and inter-area population movements, along with features attracting collective movement within and across different areas, are helpful for predicting variation in crime at the aggregate level (Browning et al., 2017; Hipp & Kim, 2019; G. Song et al., 2023). However, given the theoretical necessity of considering collective mobility patterns and the limited empirical use of cellphone locations to measure them, prior research does not tell us how successful such methods can be in estimating crime variations in specific areas, such as Baltimore. Therefore, I integrate indicators from the traditional neighborhood approach (i.e., residential mobility) with those from the situational opportunity perspective (i.e., dynamic population flow) to examine the potential relationships between collective mobility patterns and neighborhood crime. Specifically, I present my first research question:

RQ1: Are collective human mobility patterns significantly associated with crime rates in Baltimore?

Drawing on the theoretical framework from the previous chapter, I define the overall collective mobility patterns in specific areas as reflected by their levels of residential turnover and the magnitude of both inward and outward mobility flows. Social disorganization theory posits that neighborhoods with high levels of residential mobility experience more crime due to weakened social cohesion, reduced local awareness, diminished institutional support, and low collective efficacy (Sampson et al., 1997; Shaw & McKay, 1942). High residential mobility leads to an unstable population, which not only makes residents rate their living conditions as unsatisfactory but also fosters indifference and a reduced willingness to intervene when others face problems or needs (Stults & Hasbrouck, 2015; Valente & Medina-Ariza, 2024). Consequently, criminals are more likely to target neighborhoods with high residential mobility rates, as these areas offer less resistance and fewer organized community efforts to prevent crime (Boggess & Hipp, 2010; Sampson & Groves, 1989).

According to the broken windows thesis, visible signs of disorder—such as abandoned buildings and vacant households—signal weakened social cohesion, prompt residents to leave, and create conditions conducive to criminal activity (Wilson & Kelling, 1982). More importantly, as more residents leave the area and the population declines over time, property values fall, which in turn reduces investment in security and public services (Cui & Walsh, 2015). This also raises red flags for outsiders, signaling potential risks for both commercial and residential activities, as well as safety concerns. With fewer residents to monitor the area, neighbors become less likely to intervene in suspicious or criminal activities (Immergluck & Smith, 2006). This diminished informal social control makes it easier for crime to go unnoticed or unreported. Additionally, empty properties can become gathering spots for illicit activities, such as illicit drug use, gang activity, and illegal weapons storage (Branas et al., 2012). They ultimately create low-risk environments for criminals, with fewer witnesses or security measures (Jones & Pridemore, 2016). The perception of neighborhood decline further encourages criminals and discourages law-abiding residents from taking action, ultimately contributing to increased crime rates.

Based on social disorganization theory and the broken window thesis, I hypothesize that:

H1a: Higher residential mobility will be associated with higher rates of crime.

Second, the situational opportunity perspective argues that the flows of population movement shape the distribution of potential offenders, targets, and guardians through the concentration of residents and temporary visitors in time and space (G. Song et al., 2023; Stults & Hasbrouck, 2015). Both inward and outward population flows may act as risk factors for neighborhood safety. A high volume of inward flow brings a substantial number of visitors into a neighborhood over a short period, expanding the pool of potential targets and offenders (Cohen & Felson, 1979; Felson & Cohen, 1980). This influx reduces the physical and social distance between them, increasing the likelihood of interaction and, consequently, criminal opportunities. Locations that naturally attract large inflows—such as nightclubs, shopping malls, or entertainment venues—often show concentrations of valuable targets (e.g., individuals carrying cash or expensive belongings), making them especially appealing to potential offenders (Roncek & Maier, 1991; Tillyer & Walter, 2019a). Many of these newcomers are outsiders with little knowledge of the surrounding environment. Their presence undermines informal social control by making it more difficult for law enforcement and residents to tell who belongs and who does not (Hipp & Chamberlain, 2023). Local police have to pay extra attention to the safety of both locals and a more enormous, temporary population than they usually handle, complicating guardianship efforts and stressing public safety assets (Koper et al., 2022). Due to those reasons, a positive association may be expected between inward population flow and crime rates in Baltimore.

Outward population flow can also contribute to higher crime rates in Baltimore. As residents leave their neighborhoods for work, school, or other daily activities, the number of individuals available to serve as capable guardians is reduced. This decline in guardianship—

whether at home, on the streets, or within public spaces—lowers informal surveillance and social control (Cohen & Felson, 1979; Wickes et al., 2017). With fewer “eyes on the street,” neighborhoods become more susceptible to crime, as there are fewer observers to detect suspicious behavior or deter potential offenders (P. J. Brantingham & Brantingham, 2016; Jacobs, 1961). Moreover, those who remain behind during these outflows often belong to more vulnerable populations—such as the elderly, young children with caregivers, or economically marginalized individuals—who may lack the capacity to exercise effective social control (Rice & Csmith, 2002). Also, outward mobility can create opportunities for crime by facilitating interactions between departing residents (as potential targets) and incoming individuals (as potential offenders) seeking to exploit their departure (McMillen et al., 2019). As a result, heightened levels of outward mobility may substantially contribute to increased local crime rates.

The possibility exists that both inward and outward population flows may function as protective factors for neighborhood safety (Boivin & Felson, 2018; Felson & Boivin, 2015). On the one hand, a high volume of inward population flow directly enhances guardianship by increasing the number of visitors who serve as “eyes on the street” (Jacobs, 1961). With more people in the neighborhood, there is a greater likelihood that someone will notice, report, and respond to suspicious activity (Andresen, 2011). On the other hand, neighborhoods with a high volume of daily visitors are typically areas with active economic activity (e.g., central business districts, convention centers) or locations with facilities that encourage population movement and interaction (e.g., transportation hubs, amusement parks). Residents from different Baltimore neighborhoods have a common desire for a safe living environment. This need for security and stability becomes more critical as more visitors enter. The presence of tourists, commuters, and visitors for various other purposes demonstrates the attractiveness of Baltimore. It also reveals the importance of safe and clean public spaces to make everyone, whether a visitor or a resident, feel safe. Consequently, local residents have strong incentives to invest additional resources in crime prevention measures. Those investments may include improving road conditions, upgrading infrastructure, and implementing security measures like enhanced lighting and surveillance cameras (Doleac & Sanders, 2015; Domínguez & Asahi, 2023; Piza et al., 2019). Overall, changes in inward population flow influence criminal activity by increasing the number of potential witnesses, reporters, and helpers, while also generating incentives and resources that effectively strengthen street-level guardianship, which should reduce crime rates.

Similarly, outward population flow doesn't arise out of thin air; its volume is largely influenced by the existing local population, which includes both long-term residents and non-resident visitors in the area. Therefore, compared to other neighborhoods, those with either a large resident population or a high volume of daily visitors are more likely to experience a high volume of outward flow (Felson & Boivin, 2015). A high volume of outward population flow directly reduces the number of people in a neighborhood by removing potential victims, easy targets, and even individuals prone to criminal behavior (Cohen & Felson, 1979). I expect that this reduction in both available targets and offenders contributes to decreases in overall crime rates. Moreover, these populations don't simply leave the neighborhood; they also play a role in facilitating interactions between local residents and outside visitors, creating encounters between those departing and those newly arriving. These encounters enhance informal surveillance, as the presence of both departing individuals and new arrivals increases the number of vigilant observers, thereby reducing opportunities for crime (Andresen & Jenion, 2010). Therefore, neighborhoods with increased outward population flows are likely to experience lower crime rates due to both a diminished pool of population present and enhanced street-level guardianship in the neighborhoods (Linning & Eck, 2021; McMillen et al., 2019).

Therefore, criminological theories and prior empirical research have suggested the associations between population flows (both inward and outward) and crime rates that can operate in either positive or negative directions. However, for the ease of hypothesis testing, I propose directional hypotheses regarding the fundamental relationships between inward and outward population flows and crime rates:

H1b: Higher (inward and outward) mobility flows will be associated with lower rates of crime.

Third, I expect that the strength of the mobility-crime association differs between types of dynamic flow and crime. Apart from homicide, though both robbery and burglary involve the intent to steal property from others (individuals or households), the key difference is that robbery requires direct confrontation with the victim, using force or the threat of force. In contrast, burglary involves breaking and entering a structure, such as a house or apartment building, with the aim of avoiding direct contact with homeowners or residents (Bernasco et al., 2017; Mahfoud et al., 2021). Therefore, increased daily visitor flows create more challenges for robbers than burglars, as the greater number of people on the streets acts as an additional layer of guardianship. This makes using force (or the threat of force) less effective, as others are more likely to witness the incident and offer assistance (Connealy, 2021).

In contrast, a higher volume of outward population flow can lead residents to adopt strategies that more effectively mitigate burglary risks than robbery risks. As more people leave their neighborhoods during their daily routines, those stay-at-home residents become more vigilant, recognizing the increased safety risks associated with a reduced number of remaining residents (Browning et al., 2010; Cagney et al., 2020). This need for protection often motivates residents to organize and cooperate through traditional neighborhood watch programs or modern technological tools (Bennett et al., 2006; Garofalo & McLeod, 1989; Rosenbaum, 1987). As a result, neighborhoods with high outward population flow develop strong communication networks for sharing security information, implement technological solutions for enhanced surveillance, and coordinate closely with local law enforcement. Since burglary incidents are more likely to occur when properties are empty or occupants are asleep, the heightened vigilance and information-sharing among remaining residents increases the likelihood of interrupting burglars' actions, thereby reducing their success rate (Bernasco & Nieuwbeerta, 2005).

As a result, I propose the following hypotheses regarding the distinct effects of dynamic population flows on crime rates:

H1c: Inward population flow will be associated with larger decreases in robbery rates than burglary rates.

H1d: Outward population flow will be associated with larger decreases in burglary rates than robbery rates.

<u>Police activities, crime hotspots, and mobility-crime connections</u>

I. From place-based theories to policy practice

Criminological theories have long sought to explain why crime clusters in certain locations and to guide effective crime reduction strategies (Cohen & Felson, 1979; Shaw & McKay, 1942). Drawing on routine activities theory, Sherman and colleagues (1989) identified these micro-spatial crime concentrations as "hot spots." By focusing on locations rather than individuals, they discovered that over half of predatory crimes occur in a small percentage of neighborhoods (Sherman et al., 1989). This shift—from examining the routine activities of individuals to those of places—highlights the concept of "criminality of place" and calls for corresponding reforms in policing strategies (Braga et al., 2010; Weisburd et al., 2004).

Building on this idea, Weisburd (2015) introduced the "law of crime concentration at place." He demonstrated that crime is heavily concentrated in specific areas within a city—a pattern that remains consistent across different cities and time periods. Weisburd also emphasized that this approach not only advances our understanding of crime but also informs the development of effective crime control policies (Y. Lee et al., 2017; Weisburd, 2015). Aligned with Weisburd's call to recognize the criminality of place as a turning point in criminology, investigating the mechanisms linking crime and specific locations has become a central focus for both empirical research and policy development.

The nature of policing has also shifted from a person-focused to a location-based approach in response to changes in criminological theory. Most police departments, frequently suffering shortages of budgets and workforce, want to have their resources where they are most needed, usually in areas with high crime rates. Therefore, with support from later studies that most crimes are concentrated within a small number of hot spots, many police departments developed "hotspot policing" as an effective strategy to deal with serious crime issues in specific areas (Ariel et al., 2016; Braga et al., 2018; Gill et al., 2017; Telep et al., 2014). With various tactics applied, hotspot policing has become necessary for many police departments to deal with local crime issues cost-effectively (Braga & Bond, 2008; Koper et al., 2022; Piza et al., 2019; Ratcliffe et al., 2011; Uchida & Swatt, 2013). Moreover, this strategy has received further attention due to the reform suggestions brought by the final report of the President's Task Force on 21st-century Policing (Kearns, 2015), and the budget cuts during the COVID-19 pandemic (Alcadipani et al., 2020; Drawve & Harris, 2023; Ebbinghaus et al., 2024).

II. Neighborhood crime history and intensity of policing

Hotspot policing begins with the identification of hot spots. Traditionally, police departments have different preferences for defining crime hot spots, ranging from street intersections to large census tracts or blocks (Braga et al., 2014, 2019). They also rely on prior crime-related information, commonly the number of violent crimes or police calls during the past few years, to identify or forecast hot spots (Ratcliffe et al., 2021; Weisburd et al., 2017). The existing hotspot policing strategy employed by the Baltimore Police Department (BPD) involves analyzing the most recent five-year history, including all gun-related crimes (homicides, aggravated assaults, robberies, and non-fatal shootings), to predict crime hotspots (Harrison, 2019). These hotspots are further separated into two types: focused patrol areas, and district action team (DAT) activity zones. Focused patrol areas are specific, small locations that individual officers concentrate on to enhance patrol efforts and reduce crime. In contrast, DAT activity zones cover a broader area than these focused patrol spots. By maintaining a more structured focus, BPD administrators hope that DATs—combined with directed patrol strategies—allow the police to operate more effectively. They expect this approach to enhance the department's ability to effectively deter crime, combat gang activity, and suppress illicit drug markets in areas with the highest levels of these offenses. Together, focused patrol areas and DAT activity zones cover approximately 5 percent of Baltimore's land area, yet they have been associated with more than one-third of all firearm-related crimes in the city over the past five years (Harrison, 2019).

After identifying hotspots, the BPD assigns sector patrol officers to specific deployment zones, while district action teams (DAT) are tasked with covering larger areas within each police district. Police departments can implement a variety of strategies in hotspot areas, including traditional approaches like foot patrols and traffic control, installing CCTV surveillance cameras, adopting problem-oriented policing (POP), utilizing offender-focused deterrence strategies, enforcing zero-tolerance policies, and using license plate readers (Braga & Bond, 2008; Koper et al., 2022; Piza et al., 2019; Ratcliffe et al., 2011; Santos & Santos, 2015; Weisburd et al., 2015). Among these hotspots in Baltimore, patrol officers primarily conduct direct foot patrols, along with other activities such as business checks, knock-and-talks with known gun offenders under active community supervision, and coordination on executing priority warrants (Harrison, 2019). Prior research has indicated that a visible police presence in a hotspot for about 10 to 15 minutes per day, delivered at random, intermittent intervals, provides an effective deterrent against crime (Bland et al., 2021; Koper, 1995). This arrangement creates the perception that police enforcement can occur at any moment, making potential offenders view criminal activity in these areas as too risky (Braga et al., 2014). Based on this reasoning, BPD Patrol officers are expected to visit their assigned hotspots a minimum of three times per shift, spending 10 to 15 minutes at each location. These visits are distributed across their shifts and between responding to 911 calls. Likewise, DAT units focus on their designated larger zones, carrying out a range of proactive strategies. They also prioritize targeted arrests of key individuals suspected of involvement in violent crimes within their areas (Braga et al., 2014). After making arrests, they gather further intelligence by interviewing the individuals and sharing the information with the rest of the police department (Harrison, 2019).

Besides the hotspot policing strategy, neighborhoods with crime hotspots also receive other high-density police-led programs. Since 2007, Baltimore City has initiated the *Safe Streets* program, modeled after Chicago's *Ceasefire* program, aimed at diminishing firearm-related violence (Phalen et al., 2020; Whitehill et al., 2014). The initial evaluation of this program has shown a significant reduction effect in firearm-related homicides and nonfatal shooting incidents (Webster et al., 2013). However, the follow-up evaluation has also revealed substantial variations in the program's effectiveness across different sites (Buggs et al., 2022; Webster et al., 2013). For example, while some areas have experienced a decrease in homicide incidents, multiple sites in East Baltimore have also observed substantial increases in nonfatal shootings (Webster et al., 2013). Alongside the *Safe Streets* program and the hotspot policing strategy, the city has recently introduced a new focused deterrence approach known as the *Group Violence Reduction Strategy* (GVPS). This initiative directs resources toward individuals deemed to be at the highest immediate risk of involvement in gun violence (Papachristos & Kirk, 2015). The aim is to reduce homicides and non-fatal shootings while also improving community-police relationships (Crime and Justice Policy Lab, 2022).

Given the strong connection between police presence and local crime history, especially in crime hotspots, the relationship between collective mobility patterns and crime incidents may differ depending on the level of police activity within neighborhoods (P. J. Brantingham et al., 2020; Malleson & Andresen, 2015). On the one hand, police activities can weaken the connections between collective mobility patterns and neighborhood crime. The police force is commonly viewed as the primary source of guardianship, as crime fighters for law enforcement and neighborhood safety protection (Koper et al., 2022). To play these roles, the police allocate their time and resources to neighborhoods in various ways, including frequent street patrols, installing surveillance cameras, conducting stop-and-frisk operations, and taking targeted actions against specific individuals (Buckler & Higgins, 2016; Koper et al., 2022; Rosenfeld et al., 2014). With substantial numbers of individuals coming into and out of various neighborhoods, those areas with increased police presence also demonstrate heightened vigilance in monitoring potential illicit activities (Piza et al., 2020; Piza & Connealy, 2022). These heightened security measures can reduce the attractiveness of potential targets brought by dynamic population flows and high residential turnover, pushing potential offenders to reassess the likelihood of success for their criminal actions (Semenza et al., 2022).

On the other hand, increased police activities may strengthen the relationship between collective mobility patterns and crime incidents. Police officers do not randomly select locations or neighborhoods for patrols or implement policing strategies. Instead, they often increase patrol frequency and use various strategies in crime hotspots, as highlighted by numerous studies (Ariel et al., 2016; Braga & Bond, 2008; Koper, 1995; Sherman et al., 1989). These hotspots, consistently plagued by high crime rates, are perceived as favorable locations for criminal activities, offering offenders great confidence in the likelihood of their success. Owing to their complex criminal background, those areas with high coverage of crime hotspots continue to attract offenders by offering abundant opportunities to choose targets, acquire criminal tools, and evade law enforcement (Bowers, 2014; G. Song et al., 2019). Although the presence of law enforcement within those crime hotspots may discourage criminal behavior, it does not eliminate crime; instead, it may increase its visibility, strengthening the observed connection between mobility and crime (Ashby & Tompson, 2017; Koper, 1995; Santos & Santos, 2015; Wilcox & Cullen, 2018). With limited resources, police are also compelled to concentrate their patrols on crime hotspots, potentially leaving other parts of neighborhoods more vulnerable to criminal victimization, especially as the flow of visitors and residents increases (Andresen & Malleson, 2015; Gelman et al., 2007; Telep et al., 2014). Furthermore, areas characterized by a significant presence of hotspots and elevated residential mobility may attract potential offenders, who perceive that community members do not care about the safety of others and are unlikely to take action (Lanfear, 2022; Magee, 2020). The interconnections among collective mobility patterns, police activities, and crime incidents necessitate that communities evaluate the potential effects of police activities on the interplay between mobility and crime.

III. Exploring the spatial variations for mobility-crime connections

Given the lack of empirical research on the link between collective human movement and crime and law concentrations, I raised my second research question to test the potential moderating role of police patrol activity coverage between collective mobility patterns and crime incidents:

RQ2: Does the relationship between collective mobility and crime vary by the distribution of police patrol activities?

I expect to find a strong positive relationship between police activity levels and crime rates in Baltimore for two main reasons. First, BPD's hotspot policing strategy has officers concentrating their resources in areas identified as crime hotspots (Harrison, 2019). When crime incidents occur, police deploy swiftly and focus their efforts on these locations (Ratcliffe et al., 2011). This reactive approach naturally leads to high police activity in areas experiencing more crime - as criminal incidents increase, police presence and response intensify accordingly (Ratcliffe, 2004; Sherman et al., 1989). Second, increased police presence in an area typically leads to more crimes being detected and documented - a phenomenon known as the "recording effect" (J. MacDonald et al., 2016; Pina-Sánchez et al., 2023). When officers patrol crime hotspots more actively, they're likely to discover and record incidents that might otherwise go unreported (Ashby & Tompson, 2017; Koper, 1995). This can make it appear as though crime rates have increased in these neighborhoods, even if the actual amount of criminal activity remains unchanged. So, both the reactive deployment strategy and the recording effect contribute to a positive association between police activity and reported crime rates. The relationship reflects both how police respond to neighborhood crime history and how their presence affects crime detection and reporting.

Therefore, I propose the following hypotheses regarding the effects of police activity intensity on crime rates:

H2a: Neighborhoods with high levels of police patrol activities will have higher crime rates compared to neighborhoods with low levels of police patrol activities.

I also expect the relationship between collective mobility patterns and crime rates to vary as police activity intensifies. First, increased police presence can strengthen the positive link between residential mobility and crime rates. Crime hotspots identified by law enforcement influence offender decision-making, leading potential criminals to perceive these areas as having indifferent residents and weak community intervention (H. Lee & Perkins, 2023). Moreover, offenders gain confidence from past successful crimes in these locations, reinforcing their preference for neighborhoods with high turnover and extensive crime hotspot coverage (Lanfear, 2022; Magee, 2020). The combination of frequent resident turnover and concentrated police attention makes these areas attractive for future criminal activities (Semenza et al., 2022).

Second, I expect inward population flow to have a weaker negative association with crime rates in areas with enhanced police activity. While a visible police presence can attract more visitors by creating a perception of safety, the influx of strangers can strain local security measures (Andresen, 2011). A high volume of incoming population flow forces law enforcement to prioritize certain areas, leaving other parts of the neighborhood more vulnerable to crime (Ratcliffe et al., 2011). Compared to other neighborhoods, criminals may find more opportunities in those high-policing areas due to security gaps and the ability to blend into crowds, making it easier to evade detection and escape (Bernasco & Nieuwbeerta, 2005)

Third, I expect outward population flow to have a weaker negative relationship with crime rates as police patrol activity increases. Although a large number of people leaving an area could mean more potential witnesses, it also reduces the ambient population available to act as guardians or report crimes. This creates opportunities for offenders to commit crimes more easily (Bernasco et al., 2017). Additionally, outward flow facilitates key elements of certain criminal actions (e.g., robbery) by increasing face-to-face encounters between offenders and potential victims, often followed by force. The persistent concentration of crime in heavily policed neighborhoods further reinforces this pattern, as these areas attract and condition offenders for future crimes (Bowers, 2014; G. Song et al., 2019).

Drawing on these expectations, I further hypothesize that police patrol intensity moderates the relationship between collective mobility patterns and crime rates, in addition to its main effect:

H2b: the positive association between residential mobility and crime rates will be stronger in neighborhoods with high levels of police patrol activities compared to those with low levels.

H2c: the negative association between (inward and outward) population flows and crime rates will be weaker in neighborhoods with high levels of police patrol activities compared to those with low levels.

Time, human mobility, and mobility-crime connections

I. The temporal dynamics of human mobility and crime

As human mobility represents people's movement across space and time, monitoring its uneven spatial distribution alone is insufficient. Prior research suggests that it is also necessary to examine human mobility's temporal dimension, and its connections to crime periodicity (Cohn & Breetzke, 2017). For example, social disorganization theory and the broken window thesis consider changes in human mobility, like residential turnover, to be a gradual, long-term process (Shaw & McKay, 1942; Wilson & Kelling, 1982). Thus, their supporters see the influence of movement patterns on neighborhood crimes as slow-moving and likely not apparent without long-term observations. By contrast, environmental criminologists view variations in human mobility as more dynamic and rapid, producing relatively short-term effects (P. J. Brantingham & Brantingham, 2016; Cohen & Felson, 1979). As a result, in the eyes of environmental criminologists, with the progress of daily human routines, the conditions for committing crimes may be satisfied quickly and implemented by motivated perpetrators. The difference between these two types of mobility highlights the different foci of the neighborhood and situational opportunity approaches. It further reminds researchers of the need to consider the impact of collective human mobility patterns on criminal behaviors over different time spans.

When only using residential mobility as the indicator of collective mobility patterns, prior studies have largely neglected the potential temporal variations in its relationship with neighborhood crime incidents (Braakmann, 2023; DeLuca et al., 2019; Hipp, 2010). This is primarily influenced by: 1) the characteristics of the measures, as shaped by the corresponding theoretical framework, 2) the time units applied, and 3) the duration of the study. The traditional neighborhood approach views residential mobility as a structural neighborhood condition, assuming it remains relatively static over a given period (Sampson et al., 1997; Shaw & McKay, 1942; Wilson & Kelling, 1982). The widespread use of cross-sectional designs in existing studies has limited the ability of researchers to assess temporal variations in the relationship between residential mobility and crime (Boggess & Hipp, 2010; H. Lee & Perkins, 2023). Even in longitudinal studies, despite the availability of various methods to measure residential mobility, the smallest time units typically examined are years or decades (Boggess et al., 2013; Braakmann, 2023; Hipp & Chamberlain, 2023; C. M. Katz et al., 2013). Additionally, most panel studies focus on the reciprocal relationship between residential mobility and various types of crime, as well as the trends in crime rates over time in response to changes in the level of residential mobility (Braakmann, 2023; Hipp & Chamberlain, 2023). As a result, temporal fluctuations in the relationship between residential mobility and crime incidents are often either controlled for in the analytical model or omitted from the primary analysis.

By incorporating dynamic population flow as the primary measure of collective mobility patterns, recent research has increasingly emphasized its relationship with the varying distribution of crime opportunities across different periods (Berg et al., 2016; Bernasco et al., 2017; Hipp & Kim, 2019; Szkola et al., 2021). This shift is primarily driven by the transition from the traditional neighborhood approach to the situational opportunity perspective. In the latter framework, collective population movement is no longer viewed as a structural condition but rather as a bridge linking neighborhood factors and land use classifications to the interactions among potential offenders, targets, and guardians. This dynamic, in turn, facilitates the emergence of crime opportunities that may lead to actual criminal behavior (P. Brantingham & Brantingham, 1995; Cohen & Felson, 1979). Since this intersection occurs throughout urban residents' daily routines, with individuals visiting multiple locations and staying at each for a certain period within a single day, collective mobility should be viewed as a dynamic process (Browning et al., 2021; Cagney et al., 2020). Additionally, new data sources and methodological advances have made it possible to track population movement in smaller time units. The emergence of innovative data sources, such as geo-referenced mobile device location data, provides researchers with more detailed, representative, and accurate measures of directional dynamic population flows (Kang et al., 2020; Levy et al., 2020; Sampson & Levy, 2020; G. Song et al., 2019). These measures can capture and reflect population movement across various geographical scales (e.g., census block groups, census tracts, counties) within time frames as short as days, hours, or even minutes. Therefore, the theoretical foundation provided by the situational opportunity perspective, coupled with advancements in data sources and measurements, creates the necessary conditions for exploring the temporal variations in the mobility-crime connection more deeply than before.

II. From season to day: mobility-crime connections

Existing studies on temporal variations in the mobility-crime connection for dynamic population flows have focused on different time spans. However, within this subsection, I limit my major focus to three dimensions: the month or season of the year, the day of the week, and the time of day.

First, seasonal variation exists within the relationship between mobility and crime (Lab & Hirschel, 1988). For example, high and low temperatures during summer and winter affect mobility flows, altering people's travel distances, transportation choices, and routes, thus influencing neighborhood crime rates (Field, 1992). In summer, increased outdoor activity and visits to air-conditioned spaces create attractive opportunities for personal contact crimes, such as homicides, robbery, and firearm-related violence (Landau & Fridman, 1993; Szkola et al., 2021). Conversely, in winter, travel preference for indoor locations or warmer destinations reduces opportunities for street robberies but increases the risk of burglary. This shift creates conditions where potential offenders can target valuable possessions in densely populated indoor spaces or popular tourist attractions (Linning, 2015; McDowall et al., 2012). High-traffic areas like train stations may face increased crime risks during colder months as people seek shelter from harsh weather, leading to overcrowding (Gallison & Andresen, 2017; Zahnow, 2023; H. Zhang et al., 2022). Distracted travelers bundled in heavy clothing create opportunities for criminals, particularly burglars, to steal property unnoticed (Ceccato & Uittenbogaard, 2014). The uneven distribution of holidays throughout the year draws significant mobility flows to popular tourist areas, raising crime risks during events like concerts, sports games, and festivals such as New Year's Eve and Halloween in the U.S. (Billings & Depken, 2012; Cohn & Rotton, 2003; Towers et al., 2018). However, the mobility-crime connection may weaken during holidays due to enhanced guardianship. Law enforcement, shop owners, and amusement park management often implement heightened security measures to address the anticipated increase in population flows (de Melo et al., 2018).

Second, the mobility-crime connection may vary depending on the day of the week. Individuals often travel to workplaces during weekdays and stay at home or other places for weekend entertainment and leisure (Andresen & Malleson, 2015; W. D. Lee et al., 2021; G. Song et al., 2023). As a result, different trends may be present for mobile-crime connections between weekdays and weekends. For example, weekend crime rates may be higher in areas with lots of nightlife and entertainment owing to the larger number of people and increased alcohol consumption in these areas (Grönqvist & Niknami, 2014; Gruenewald et al., 2023; Pridemore & Grubesic, 2012). Using data from Vancouver, Anderson and Malleson (2015) have found that assaults climb in the city's bar district while vehicle thefts soar in the downtown and recreational parking lots during weekends. Intraweek fluctuations in population movement can also significantly impact the distribution and composition of people engaged in business, education, tourism, and other activities across different urban neighborhoods, thereby influencing changes in crime rates (Felson & Boivin, 2015; Stults & Hasbrouck, 2015). Tucker and colleagues (2021) have found that higher commuter flows are associated with fewer violent incidents during weekdays but contribute to more private conflicts during weekends. Moreover, Hipp and Kim (2019) have found that street segments with fewer regular working employees can attract more robberies during weekend evenings. Prieto Curiel (2023) has found that bank robberies in Mexico City are most common on Thursdays. This is attributed to the high level of activity across the city and the increased number of bank users making withdrawals, deposits, and other transactions in preparation for Friday and the weekend (Prieto Curiel, 2023).

Third, mobility-crime connections may vary based on the time of the day. Most individuals travel to their workplaces in the morning and return home after work hours (Bernasco & Block, 2011; Felson & Boivin, 2015; Liu et al., 2022). Therefore, the quantity of mobility flows into commercial and industrial areas can increase in the morning (G. Song et al., 2018). In contrast, mobility flows returning to residential neighborhoods become more substantial during the afternoon or evening (Domínguez & Asahi, 2023). The variations in human mobility patterns from morning to night create differential space for the emergence of criminal opportunities (Hanaoka, 2018). Crime rates, for example, may be greater in the evenings and at night, when circumstances (e.g., darkness and dim street lights) can facilitate and provide cover for crimes such as burglary and robbery (Coupe & Blake, 2006; Doleac & Sanders, 2015). While some studies confirm the intraday variations in the mobility-crime relationship (Hanaoka, 2018; W. D.

Lee et al., 2021; Liu et al., 2022; Tucker et al., 2021), others, such as Bernasco and colleagues (2017), argue that population movements do not influence robbery perpetrators' location choices throughout the day.

III. Exploring the temporal variations for mobility-crime connections

Given the temporal fluctuation of mobility and its associated impact on crimes, I raise my third research question regarding the temporal dimension of human mobility and crime:

RQ3: Does the relationship between collective mobility and crime vary over time?

First, I expect the relationship between collective mobility patterns and crime rates to vary across seasons. Summer typically features milder weather and longer daylight hours than other seasons (Wesolowski et al., 2017). Those conditions encourage people to go outside more often and engage with others socially. This can enhance guardianship and informal surveillance by drawing more witnesses, bystanders, and potential crime reporters to the area compared to other seasons (Zufiria et al., 2018). The profile of those travelers may also differ by season. In colder months, population movement may be more often driven by family or business needs, unlike the leisure or tourism-related flows that are more common in summer, which can impact urban dynamics and crime rates differently (Boivin & Felson, 2018; G. Song et al., 2023).

Besides, the large influx of people arriving in or leaving the city for vacations or holiday travel during summer leads to significant shifts in the local residential environment. With many strangers entering the area and few residents at home, those who remain must stay vigilant and rely heavily on security measures such as alarms, home security systems, and community surveillance to maintain adequate guardianship (Mahfoud et al., 2021; Newton et al., 2014; Santos & Santos, 2015). Otherwise, summer may present even more opportunities for potential offenders than other seasons, as many homes are temporarily unoccupied, and most incoming visitors are unfamiliar with the area, reducing their ability to assist or alert the police (Piza & Carter, 2018; Rey et al., 2012).

Given the potential existence of seasonal variations within the relationship between dynamic population flows and crime rates, I propose the following hypothesis:

H3a: The negative relationship between high inward and outward population flows and low crime rates will be stronger during summer (June through August) than in other seasons.

Second, I expect the relationship between collective mobility patterns and crime rates to vary across days of the week. On weekdays, when most people commute for work or school, they focus primarily on reaching their destinations, making them less aware of their surroundings. This reduced environmental awareness creates more opportunities for offenders to encounter potential targets, weakening the protective effect that large visitor flows might otherwise provide as an additional layer of guardianship (Andresen & Malleson, 2015; Bernasco et al., 2017; Tucker et al., 2021). In contrast, weekends are typically reserved for rest and leisure activities, meaning inward population flows are more likely to involve people engaging in recreational and social activities such as shopping, dining, and entertainment (Boivin & Felson, 2018; Felson & Boivin, 2015). Weekend crowds remain in public spaces longer rather than simply passing through, leading to increased and sustained surveillance (Guo et al., 2022). Visitors are also more likely to actively observe their surroundings (W. D. Lee et al., 2021; G. Song et al., 2023). As a result, the larger and more vigilant crowds on weekends, brought by inward population flows, may reduce the perceived chances of success for potential offenders, ultimately discouraging them from targeting those areas.

Likewise, when people leave their neighborhoods, its associated changes in target availability and guardianship can also influence crime rates differently between weekdays and weekends. On weekdays, as many residents leave, informal surveillance in residential areas declines, making them more vulnerable to crimes such as burglary (Mahfoud et al., 2021; Rey et al., 2012; Tucker et al., 2021). In contrast, the increased daytime population in business districts may lead to crimes like robbery or larceny due to the higher concentration of potential targets (Bernasco et al., 2017; Connealy, 2021; Hipp & Kim, 2019). On weekends, the majority of residents choose to stay near their homes, which can reduce opportunities for certain crimes but may also concentrate others in busy public spaces (W. D. Lee et al., 2021; G. Song et al., 2023).

Due to the mobility dataset using a daily time unit (24 hours), I cannot analyze finer, within-day temporal variations in mobility-crime relationships. Aside from this deficiency, I propose one additional hypothesis that explores the intraweek variations in the relationship between mobility and crime:

H3b: The negative relationship between high inward and outward population flows and low crime rates will be stronger on weekends (Saturday and Sunday) than on weekdays.

Chapter 4: The Current Study

To answer the research questions and test relevant hypotheses identified in the previous chapter, the current study focuses on Baltimore, the largest city in Maryland. This city, with a population of nearly 600,000, suffers from homicide and firearm violence rates significantly higher than both state and national averages (Crifasi et al., 2022; Milam et al., 2016).

In the current study, I define neighborhoods in terms of census tracts and treat them as the geographical unit of analysis. As a permanent county subdivision, a census tract, to some extent, can be viewed as an officially defined neighborhood. However, residents' perceptions of neighborhoods may differ greatly from those of census tracts (Hipp, 2010; Linning et al., 2025). I choose to use census tracts as the unit of analysis for three reasons. First, the information about mobility is not accessible at a level lower than the census tract. Second, the census tract is the most commonly used unit of analysis for other data in the study, including land area, land use, and community characteristics, which makes it convenient and practical to aggregate information from various sources. Third, previous research has extensively used census tracts as a proxy for neighborhoods, providing a rich foundation upon which the present study can draw (O'Brien et al., 2022; Ranson et al., 2019; G. E. Tita et al., 2006).

There are 200 census tracts within the city boundary of Baltimore, each assigned a unique numerical identifier known as the Federal Information Processing Series (FIPS) code. However, I include only 198 census tracts in the final sample. Two tracts are excluded: one contains the city jail, detention center, and other correctional facilities, while the other is a fully industrialized area with no reported residential population, according to the American Community Survey. To minimize the potential impact of the COVID-19 pandemic, the current study focuses exclusively on the year 2019 (Cheng et al., 2025).

Data

This study includes information from four sources. I discuss each in the sections that follow.

Crime information. First, I obtain data on Part 1 crime incidents in 2019 from the *Open Baltimore* website (https://data.baltimorecity.gov/). I gather several elements from Part 1 crime data, including precise time of offenses, location (i.e., address, latitude, and longitude coordinates), offense classification, information on weapons, and geographical coverage of police districts. I also obtain detailed coverage of crime hot spots from the Baltimore Police Department.

Mobility information. The second source, primarily for dynamic population flow information, came from the *Multiscale Dynamic Human Mobility Flow Dataset in the U.S. during the COVID-19 pandemic* (Kang et al., 2020). Using data from the *SafeGraph* COVID-19 Data Consortium, this open-source dataset tracks the mobility trajectories of millions of cell phone users from January 1, 2019, to December 31, 2021. It follows specific steps to construct origin-destination (O-D) flow data. First, *SafeGraph* identifies each mobile phone user's home location by analyzing the device's typical nighttime location (between 6 p.m. and 7 a.m. local time) over the previous six weeks. After applying differential privacy to device count metrics, such as adding Laplacian noise, each user's home location is then aggregated to the census block group (CBG) level. This process is designed to protect privacy and prevent the identification or tracking of individual records (Cheng et al., 2025; Kang et al., 2020).

Second, during each day, *SafeGraph* tracks and records the number of unique mobile phone users residing in origin CBG who travel to a different CBG as their destination. The user's GPS pings are clustered, and only clusters with multiple pings (not a single trajectory point), lasting at least one minute within the destination CBG, qualify as a "visit." Third, the dataset groups and sums the daily mobile phone-based visitors between CBGs, then aggregates the data to three geographical scales (census tract, county, and state). It finally offers data on dynamic origin-to-destination (O-D) visitor flows in daily and weekly formats based on these place visits (Kang et al., 2020; Li et al., 2021).

I use this data in daily format at the census tract level for Baltimore in 2019. The data includes detailed information such as geographical identifiers for origins and destinations, longitude and latitude, estimated visitor flows between each pair of census tracts (as origin and destination), and the number of unique devices within each tract. By aggregating these records, I can measure daily, weekly, and monthly average counts of inward and outward mobility flows for each Baltimore neighborhood.

Community structural characteristics. The third data source, the *American Community Survey* (ACS), administered by the U.S. Census Bureau, provides information on the structural characteristics of all census tracts within Baltimore during 2018. All characteristics are based on 5-year estimates and cover various aspects of Baltimore City, such as the total residential population, poverty status, vacant housing, percent young, and educational attainment. The information relevant to residential turnover/mobility also comes from this data source.

Land area and use purpose. I obtain land area information from the U.S. Census Bureau through the *TIGERweb* platform, which provides the land size for each Baltimore census tract in square meters. I also gather land use data from the Baltimore City Department of Planning website, including zoning codes and maps. The zoning information specifies the designated use of land, including categories such as retail, residential, institutional, industrial, transportation, etc. Using the land area data, I can convert the land use information into several measures that show the percentage of each specific land use purpose within each neighborhood.

<u>*Measures*</u>

Table 4.1 provides a detailed overview of the variables, including their descriptions and corresponding descriptive statistics. Corresponding to each section of Table 4.1, I introduce the primary outcomes, key predictors, potential moderators, and additional covariates included in the analytic model.

I. Primary outcome(s)/dependent variable(s)

Primary outcome(s). The primary objective is to analyze the total number of crime incidents recorded in each Baltimore neighborhood in 2019. The first section of Table 4.1 presents the key outcomes of this study, which include the total number of (1) homicides, (2) robberies, and (3) burglaries in 2019. These crime types are strategically selected because research and criminal justice practice commonly classify homicide as a primarily violent crime, burglary as mainly a property crime, and robbery as a crime that involves both violent and property elements. Compared to other common offenses, these crimes are more consistently reported and accurately measured (Blumstein et al., 1991; Cheatwood, 1988; Lynch & Addington, 2006; Messner, 1984). Furthermore, they have been extensively examined in prior studies (e.g., Brame et al., 2017; Lauritsen et al., 2016; Rey et al., 2012; Rosenfeld & Fornango, 2007; Rosenfeld & Messner, 2009), allowing for reliable comparisons. For the longitudinal analysis, I also generate daily, weekly, and monthly data for each crime type.

Table 4.1

Descriptive statistics for neighborhood characteristics in Baltimore City (N=198)

Variables	Description	M(SD)	Min	Max
Crime and police activity				
Homicide				
Total (2019)	Total counts of homicides in 2019	1.72 (2.05)	0	10
Lagged (2014-18, 5-yr average)	Average counts of homicides from 2014 to 2018	1.51 (1.42)	0	6
Robbery				
Total (2019)	Total counts of robberies in 2019	24.93 (27.06)	0	326
Lagged (2014-18, 5-yr average)	Average counts of robberies from 2014 to 2018	24.75 (20.89)	.40	232.60
Burglary				
Total (2019)	Total counts of burglaries in 2019	26.86 (16.36)	2	114
Lagged (2014-18, 5-yr average)	Average counts of burglaries from 2014 to 2018	36.07 (19.86)	2.60	102
Police activity /BPD hotspot coverage	Percentage of neighborhood areas classified as having intense police patrol activities	10.04 (16.52)	0	83.38
Collective mobility patterns				
Residential mobility				
Relocated in the past five years	Percentage of population age 5+ relocated or resided in a different residence during the past 5 years	16.48 (8.51)	0	66.29
Dynamic population flows				
Inward population flows (daily average)	The total number of dynamic population flows entering each census tract within a single day during 2019	6336.01 (5002.71)	1372.01	52944.70
Outward population flows (daily average)	The total number of dynamic population flows departing from each census tract within a single day during 2019	6025.15 (2881.53)	43.59	14437.71
Structural characteristics				
Disadvantage (index)	Average of the z-scores of the following six variables	0 (.82)	-1.63	1.60
Joblessness	Percentage of population aged 16-64 unemployed or out of the labor force	36.83 (14.36)	8.94	100
Professional or managerial occupations	Percentage of employed civilian population age 16+ working in professional or managerial occupations (reverse-coded)	38.42 (20.02)	0	83.16

Variables	Description	M(SD)	Min	Max
No high school diploma	Percentage of population aged 25+ who do not have a high school diploma or equivalent	16.10 (9.54)	0	43.48
Female-headed households	Percentage of households that are female-headed families	22.84 (13.70)	0	65.58
Secondary sector low-wage jobs	Percentage of employed civilian population age 16+ employed in the secondary occupations with the lowest average incomes	24.23 (11.99)	0	58.90
Below the poverty line	Percentage of population that is below the poverty line	23.41 (14.21)	0	100
Immigrant prevalence (index)	Average of the z-scores of the following three variables	0 (.94)	-.89	4.72
Foreign-born	Percentage of the foreign-born population	7.64 (6.84)	0	37.17
New immigrants	Percentage of the foreign-born population entering the US in 2000 or later	4.51 (5.01)	0	24.93
Linguistic isolation	Percentage of households in which no one age 14+ speaks English fluently at home	1.92 (2.99)	0	19.13
African American population	Percentage of non-Hispanic African American population	61.92 (33.84)	0	99.35
Hispanic/Latino population	Percentage of Hispanic/Latino population	5.01 (7.27)	0	44.90
Young males age 15-24	Percentage of the male population aged 15-24	6.07 (4.39)	0	38.33
Housing vacancy	Percentage of vacant/unoccupied housing units	19.88 (12.06)	0	60.84
Renter-occupied housing units	Percentage of occupied housing units that are renter-occupied	53.03 (20.06)	0	100
Land use information				
Retail	Percentage of land areas designated for retail purpose	8.65 (11.84)	0	83.56
Residential	Percentage of land areas designated for residential purpose	58.29 (27.41)	0	99.53
Institutional	Percentage of land areas designated for institutional purpose	10.39 (12.79)	0	79.76
Industry	Percentage of land areas designated for industrial purpose	6.36 (12.80)	0	73.02
Transportation	Percentage of land areas designated for transportation purpose	2.92 (4.02)	0	22.32
Other purposes	Percentage of land areas designated for other purposes	13.38 (18.28)	0	84.63

Note. Standard deviations in parenthesis

Lagged outcome(s). I also use data on homicide, robbery, and burglary from 2014 and 2018 to create 5-year averages of prior crime counts. This allows me to include lagged crime outcomes for each neighborhood.

Exposure variable. Including an exposure variable—representing the population over which crime incidents are observed—is essential in regression models with count data (Boivin, 2018). This variable allows me to convert raw crime counts into standardized crime rates (e.g., crimes per 100,000 residents), ensuring fair comparisons across neighborhoods with different population sizes. Without adjusting for exposure, differences in crime counts may simply reflect the varying neighborhood populations for crimes to occur, rather than actual differences in underlying crime rates influenced by other factors. In other words, neighborhoods with larger populations might appear to have more incidents merely due to having more residents (and visitors). By incorporating an exposure variable, my analysis can more accurately reflect true crime rates and produce valid and interpretable results.

Prior studies often use the total residential population within each neighborhood as the exposure variable (Logan & Stults, 1999; Miethe et al., 1991; Stafford & Galle, 1984). However, relying solely on the residential population does not fully capture the potential population at risk of crime victimization (Andresen, 2011; G. Song et al., 2023). The daily population of a neighborhood includes not only its residents but also visitors, both contributing to the overall exposure to crime. To address this issue, Andresen (2011) introduces the concept of *ambient population*, referring to the total number of people present in a particular area at a specific time, including residents and non-resident visitors. Unlike the residential population, which only accounts for those who live in the area, the ambient population provides a more dynamic measure of human activity and crime exposure, reflecting daily fluctuations in population density (Boivin & Felson, 2018; G. Song et al., 2023).

This study defines the ambient population as *the combined total of the residential population and the average daily inflow of dynamic population movements into each neighborhood*, derived from the American Community Survey and the Multiscale Dynamic Human Mobility Flow Dataset.

II. Primary predictor(s)/independent variable(s)

Collective mobility patterns. The second section of Table 4.1 introduces the three primary predictors I use to measure collective mobility patterns. The first measure, residential mobility/turnover, is drawn from the 2014–2018 American Community Survey 5-year estimates and represents *the percentage of individuals aged five and older who have moved or resided in a different home during the past five years.*

Based on its direction, I divide the measure of dynamic population flows into two types: 1) *inward population flow* and 2) *outward population flow*. For each neighborhood, I define inward population flow as the total number of visitors coming into the area from other neighborhoods/census tracts on a single day. Similarly, I define outward population flow as the total number of visitors leaving each neighborhood and traveling to other neighborhoods on a single day. These serve as the second and third predictors of collective mobility patterns.

However, using origin-to-destination (O-D) visitor flows to measure these without adjustments has several limitations. First, the *Multiscale Dynamic Human Mobility Flow Dataset* tracks the daily movement of mobile phone users, not the general U.S. population. *SafeGraph* mobile users in this dataset represent only about 10% of the U.S. population. Li and colleagues (2024) have also found that, in the *SafeGraph* dataset, areas with relatively low population coverage are typically situated in regions of the Northeast and West with high population density. Specifically, for Baltimore during 2019, the average sampling rate—calculated by dividing the total number of devices in each census tract by the corresponding population—is between 5% and 10%, indicating a low-to-medium level of population coverage (Z. Li et al., 2024). Second, the ratio of unique mobile devices detected in each census tract to the total resident population varies significantly across different areas. Third, an empirical concern arises from the strong correlation between existing inflow and outflow measures in Baltimore, with a Pearson correlation coefficient exceeding 0.7. Since both measures rely on GPS signals from mobile device location data, neighborhoods with more incoming visitors are likely to have higher levels of outgoing flow data. This high correlation makes it difficult to include both measures in the same regression models, as it obscures their individual effects and can introduce bias into the estimated coefficients and standard errors.

To address those concerns, I create two "weighted" visitor flow measures to estimate the daily inward and outward population flows. I measure *inward population flow* as the total number of dynamic population flows entering each census tract within a single day during the calendar year 2019. For each day, I calculate the total number of inward population flows using the following formula:

$$inflows(d) = \sum inflows(o_i, d) = \sum visitorflows(o_i, d) \times \frac{pop(o_i)}{devicecount(o_i)}$$

Here $inflows(d)$ is the total projected dynamic population flows to the given census tract d, while $inflows(o_i, d)$ indicates the projected dynamic population flows between the census tract o_i as the origin and the census tract d as the destination. $visitorflows(o_i, d)$ represents the volume of visitor movements originating from a given census tract o_i to the target census tract d. $pop(o_i)$ represents the total number of residents living in the census tract o_i based on the

American Community Survey, and $devicecount(o_i)$ equals the counts of unique mobile devices identified within the census tract o_i.

I also measure *outward population flow* as the total number of dynamic population flows departing from each census tract as the origin within 24 hours during the same year. For each day, I calculate the total number of outward population flows using the following formula:

$$Outflows(o) = \sum Outflows(o, d_i) = \sum visitorflows(o, d_i) \times \frac{pop(o)}{devicecount(o)}$$

Term $outflows(o)$ refers to the total projected dynamic population flows departing from the specified census tract o, $Outflows(o, d_i)$ estimates the volume of dynamic population flows from the census tract o to any specific census tract d_i, $visitorflows(o, d_i)$ measures the volume of visitor flows from the specified census tract o as the origin to any single census tract d_i as the destination, $pop(o)$ equals the total number of residential population reported in the census tract o as the origin, while $devicecount(o)$ is the number of unique mobile devices detected in that census tract o.

Kang and colleagues (2020) first developed this metric and evaluated its distribution, revealing a promising consistency with various other mobility data sources. Furthermore, previous studies have indicated that *SafeGraph*'s samples closely align with actual census populations across multiple socio-economic characteristics, making them a reliable representation of the overall population for capturing collective human mobility patterns (González et al., 2008; Kang et al., 2020; Noi et al., 2022). Therefore, drawing on insights from their research, I adopt those measures to estimate the average short-term population flows entering and leaving each neighborhood on a daily basis. These alternative measures also significantly reduce the high correlation between inflow and outflow, thereby enabling both factors to be included in subsequent analyses without posing serious multicollinearity concerns.

For longitudinal analyses, I convert the measures of inward and outward population flows into different formats, including: 1) daily counts, 2) weekly counts, and 3) monthly counts during the calendar year 2019.

III. Moderator(s) and covariates

Police patrol activity intensity indicator. Accurately capturing the intensity of different types of police activities within a specific location or neighborhood is a challenging task. While there have been efforts to use GPS pings from police officers' mobile phones to measure changes in police activity intensity, such a measure did not exist in Baltimore before the pandemic, nor was there any official or third-party source that reliably tracked this data. As a result, I have to use a proxy variable: the coverage of BPD crime hotspots. Considering that 1) crime hotspots are generally smaller than the total land area of a neighborhood or census tract, 2) some hotspots may extend across multiple census tract boundaries, and 3) specific census tracts may encompass several crime hotspots, Using the shapefile provided by BPD, I create a variable indicating the percentage of land area within each neighborhood that falls within a designated BPD crime hotspot.

As outlined in the previous chapter, the BPD identifies crime hotspots using the total number of gun violence during the past five years, and adjusts their patrols and other activities accordingly in those areas. Therefore, I expect neighborhoods with high coverage of BPD crime hotspots to experience more intense police patrols and related activities than neighborhoods with low or no coverage. I recognize that this measure is far from perfect, and its use comes with certain costs, which will be discussed in more detail in the final chapter.

Seasonal and weekday/weekend indicators. I construct the seasonal indicator for longitudinal analyses to show whether a specific month, week, or day belongs to spring (March, April, and May), summer (June, July, and August), fall/autumn (September, October, and November), or winter (December, January, and February). I also create a binary indicator demonstrating whether a particular date during 2019 belongs to weekdays (Monday-Friday) or weekends (Saturday and Sunday).

Structural characteristics. Multiple covariates may confound the relationship between the primary outcome(s) and the predictor(s). Several prior studies have identified these covariates and included them in multivariate analysis (Hipp & Wickes, 2017; Kirk & Papachristos, 2011; Lowenkamp et al., 2003; Sampson et al., 1997). Therefore, I include several indicators of structural characteristics in the third section of Table 4.1.

To measure structural disadvantage, I construct a *Disadvantage* Index (Cronbach's alpha = .90) by averaging the standardized values of six indicators: (1) the proportion of individuals aged 16 to 64 fall outside the active labor force, including the unemployed, (2) the percentage of residents aged 16 and older employed in professional, managerial, or related occupations (reverse-coded), (3) the percentage of residents without a high school diploma, (4) the percentage of households headed by females, (5) the percentage of residents employed in low-wage jobs within the secondary labor market, and (6) the proportion of individuals living below the poverty threshold. To assess immigrant concentration, I generate the *Immigrant Prevalence* Index (Cronbach's alpha = .93), which is the average of three standardized variables: (1) the percentage of foreign-born residents, (2) the percentage of the foreign-born population who migrated to the U.S. in 2000 or thereafter, and (3) the percentage of households in which no member aged 14 or older is proficient in English. In addition to these indices, I include several percentage-based indicators capturing key structural characteristics, such as the proportions of *non-Hispanic African American residents*, *Hispanic or Latino residents*, *young male residents aged 15 to 24*, *renter-occupied housing units*, and *vacant or unoccupied housing units*.

Land use purposes. As presented in the final section of Table 4.1, I also include several indicators to capture variations in land use patterns. These variables reflect the percentage of land designated for *retail*, *residential*, *institutional*, *industrial*, *transportation*, and *other* uses.

I standardize nearly all primary predictors and covariates before conducting the subsequent analyses, except for the two indices. I choose not to standardize those measures, as I have previously computed each as the average standardized z-scores of the pertinent items.

<u>*Analytic strategy*</u>

I. Crime and spatial autocorrelation

This study's primary outcomes of interest are the homicide, robbery, and burglary offense count within each Baltimore census tract. However, crimes are not spread randomly throughout space; they typically follow visible geographical patterns called spatial autocorrelation (Hubert & Golledge, 1981; Legendre, 1993). Spatial autocorrelation—the degree to which crime rates or incidents cluster geographically—should be considered in statistical analysis to reduce bias and improve model accuracy (Getis, 2010; Legendre, 1993).

To assess the degree of spatial autocorrelation, I need to define spatial neighbors based on specific criteria. For this study, I use the *Queen contiguity* method, one of the most common contiguity-based spatial weight definitions (Anselin, 1988). Under this approach, a census tract is considered a neighbor of another if they share either a boundary (edge) or a vertex (corner). To represent the underlying spatial structure, I construct a row-standardized spatial weights matrix. Then, I employ two established metrics: Global Moran's I and Geary's C (Griffith & Chun, 2022; Moran, 1950). Both statistics confirm the existence of positive spatial autocorrelation across the dataset, as well as for the specific dependent variables analyzed. A preliminary analysis of residuals from the standard Poisson regression models also supports this conclusion.

II. Poisson regression with Moran Eigenvector Spatial Filtering (MESF)

In the earlier section, I have briefly discussed the need to consider varying population sizes among different neighborhoods and the benefits of using crime rates instead of crime counts to represent urban victimization risks. Consequently, previous studies have often chosen to utilize crime rates (per 100,000) as their outcome variables and apply Ordinary Least Squares (OLS) regression or its spatial variant (e.g., spatial lag regression) for analysis. Nonetheless, the straight use of crime rates as outcomes and the simple utilization of OLS regression presents several problems. First, crime incidents are rare, discrete events, making OLS assumptions of normally distributed errors inappropriate (Osgood, 2005). Second, the homoscedasticity assumption in OLS regression is violated with crime counts. For neighborhoods with higher populations, if they have more crimes, they are also likely to exhibit greater crime variances (Berk & MacDonald, 2008). Third, low base rates for homicide and highly skewed robbery distributions require special handling for zeros and complex transformations, complicating interpretation (Tillyer et al., 2023). Fourth, pre-calculating crime rate introduces ratio fallacies, as dividing crime counts by population size creates mathematical dependencies between the numerator and denominator. This can produce spurious associations if any predictors on the right side of the regression equation correlate with population size (Kronmal, 1993). It also complicates the error structure, since numerator and denominator errors are interrelated (Firebaugh & Gibbs, 1985). In addition, OLS may generate negative predicted values for crime rates, which are impossible in practice. Thus, alternative modeling strategies, such as count-based regression approaches, may better handle these methodological issues than OLS regression.

Given the count-based nature of the dependent variable, the necessity to adjust for population differences across neighborhoods, and the presence of spatial autocorrelation, this study applies a Poisson regression model with Moran Eigenvector Spatial Filtering (MESF), incorporating the ambient population as an exposure/offset term (Berk & MacDonald, 2008; Bester et al., 2011; Osgood, 2000). MESF offers an innovative approach to address spatial dependence in regression models (Dormann et al., 2007; Murakami & Griffith, 2019; Tiefelsdorf & Griffith, 2007). Though underutilized in criminological research, MESF has demonstrated strong performance and reliability in several validation studies, consistently producing unbiased and stable estimates (Chun & Griffith, 2014; Pace et al., 2013). Recent findings suggest that MESF frequently outperforms other spatial modeling strategies regarding predictive accuracy and overall model fit (Oshan & Fotheringham, 2018; Sun et al., 2021).

MESF works by introducing a set of eigenvectors into the regression models as proxies for latent spatial structures (Griffith, 2017). These eigenvectors, which are derived from the spatial weights matrix defined earlier, help isolate and control for spatial dependencies among geographically related observations (Griffith & Chun, 2019). The process begins by computing all n eigenvectors and their respective eigenvalues, where n represents the number of census tracts in Baltimore. Each eigenvector corresponds to a distinct pattern of spatial autocorrelation and remains uncorrelated with the others due to their orthogonal construction (Chun et al., 2016). From this entire set, a subset is chosen to serve as additional predictors (or filters) within the regression models. The selection process begins by keeping only those eigenvectors that show substantial positive spatial autocorrelation. A forward stepwise selection method is then employed, using indicators like the Akaike Information Criterion (AIC) and reductions in residual spatial dependence to determine which eigenvectors to retain (Chun et al., 2016). The primary objective of this selection process is to reduce residual spatial autocorrelation at each step. Following each iteration, I recalculate Moran's I on the residuals, and this process continues until spatial dependence is sufficiently reduced or effectively eliminated (Griffith & Chun, 2019). Once this condition is met, the chosen eigenvectors are integrated into the Poisson model as control variables for spatial effects. Those eigenvectors are included solely to capture the spatial structure and are not interpreted substantively; their role is to address spatial autocorrelation, and the current study does not focus on the size, direction, or significance of their coefficients (Griffith et al., 2019).

III. Cross-sectional model to assess mobility-crime connections

RQ1 *asks whether collective mobility patterns can predict crime rates*. The first step is to examine the unadjusted relationship between indicators of collective human mobility patterns and the major crime outcomes, only accounting for spatial autocorrelation, without including additional covariates and lagged outcomes. I use Pearson correlation tests and bivariate Poisson regression with MESF, and proceed with all three indicators of collective mobility patterns included. Then, I add the complete set of covariates and the corresponding lagged outcomes to each model to examine the adjusted mobility-crime relationships. The basic formula of the cross-sectional model is shown in equation (1):

$$ln\,(E(Crime_i)) = \beta_0 + \beta_1 InwardFlow_i + \beta_2 OutwardFlow_i + \beta_3 ResMobility_i + \beta_4 LaggedCrime_i + \sum \beta_j Covariate_i + \sum \beta_k EV_i + ln\,(AmbientPop_i) + \epsilon_i \tag{1}$$

Here EV_i represents the eigenvectors selected to account for spatial autocorrelation, and $ln(AmbientPop_i)$ is the log of the exposure variable, the ambient population (residents and visitors), to adjust for the population at risk, and ensures the model estimates rates (e.g., crimes per capita) rather than raw counts. In both the cross-sectional models and subsequent analyses*, I cluster the standard errors at the police district level*, as crime hotspots and police patrol assignments are nested within each district. Since these factors may vary across districts and errors within each district are likely correlated, clustering at this level accounts for these correlations (Cameron & Miller, 2015; Wooldridge, 2010).

IV. Moderation analysis and spatial variations

In **RQ2**, I explore *whether the intensity of police activities strengthens or weakens the relationship between collective mobility patterns and crime rates*. I perform a moderation analysis by creating the interaction terms between the proxy variable of police patrol activity intensity (i.e., the BPD crime hotspot coverage indicator) and each mobility factor in the full model (Hayes, 2017). I add those interaction terms individually and collectively to the primary model (as shown in equation (1)) to examine whether the effect of collective mobility flows on crime outcomes is the same across neighborhoods as the intensity of police patrol activities increases. If any interaction terms are found to be statistically significant, I conduct post-hoc analyses—such as simple slopes analysis and pairwise comparisons—to interpret the spatial variation present in the relationships between mobility and crime. As an additional step, I generate interaction plots to visually illustrate the marginal effects of the interaction terms. Due to the high correlations between the BPD crime hotspot indicator and the lagged outcomes of homicide and robbery incidents, I exclude these lagged variables from the moderation analyses for those two outcomes. However, I retain the lagged outcome for the moderation analysis related to burglary.

V. Longitudinal analysis and temporal variations

RQ3 *examines the temporal variations of the relationship between collective mobility patterns and crime*. Unfortunately, I can only examine the temporal variations within the relationship between inward and outward population flows and neighborhood crime rates during this step, as the measure of residential mobility remains constant within the year 2019. I first conduct descriptive and time series analyses to look at the fluctuations of inward and outward mobility flows and different crime outcomes across weeks or months of the year, and then across days of the week. I also check for potential signs of temporal/serial autocorrelation, meaning strong connections of the successive values for the same variable over time. The ACF (autocorrelation function plot) and PACF (partial autocorrelation function plot) suggest that temporal autocorrelation exists within the trends of inward and outward population flows and the number of crime incidents, which I should also account for in those panel models (Box et al., 2015).

Seasonal variations. I use a longitudinal Poisson regression with MESF and neighborhood-level fixed effects to analyze the relationship between inward and outward population flows and the expected weekly number of crime incidents, while also exploring potential seasonal variations in these relationships. Using a panel dataset at the weekly level ensures that there are a sufficient number of crime incidents for each observation, while also capturing intra-month and inter-week variations that can be missed with monthly data. The formula of the longitudinal Poisson regression with MESF, using weekly counts, is presented in equation (2):

$$ln\ (E(Crime_{ij})) = \beta_0 + \beta_1 InwardFlow_{ij} + \beta_2 OutwardFlow_{ij} + \beta_3 Season_{2019} + \beta_4 LaggedCrime_{ij} + \sum \beta_k EV_{ij} + ln\ (AmbientPop_{ij}) + \alpha_i + \epsilon_{ij} \quad (2)$$

The term EV_{ij} refers to the selected eigenvectors to account for spatial autocorrelation, and $ln(AmbientPop_i)$ is the log of the exposure variable. Additionally, I include a temporal lagged outcome variable (i.e., $LaggedCrime_{weekly}$, crime counts from the prior week) to control for temporal autocorrelations. I also incorporate fixed effects for neighborhoods to account for any unobserved, time-invariant characteristics specific to each neighborhood that the model does not capture (Wooldridge, 2005, 2010).

To perform the moderation analysis, I include the interaction terms between inward population flow and the seasonal indicator, as well as between outward population flow and the seasonal indicator. I add those interaction terms individually and collectively to the regression models in equation (2). If one or both interaction terms remain significant in the final models, I visualize the complex relationships among population flow, seasonal indicators, and the predicted response counts/rates of crime outcomes using interaction plots.

Weekday/weekend variations. Analyzing weekday/weekend variations in mobility-crime connections is only possible with daily data. The formula for the longitudinal Poisson regression with MESF and neighborhood-level fixed effects using daily counts is shown below:

$$ln\ (E(Crime_i)) = \beta_0 + \beta_1 InwardFlow_{ij} + \beta_2 OutwardFlow_{ij} + \beta_3 Season_{2019} + \beta_4 Weekend_{2019} + \beta_5 LaggedCrime_{ij} + \sum \beta_k EV_{ij} + ln\ (AmbientPop_i) + \alpha_i + \epsilon_{ij} \quad (3)$$

Similar to the prior analysis of seasonal moderations, the term EV_{ij} refers to the selected eigenvectors to account for spatial autocorrelation. $ln(AmbientPop_i)$ represents the log of the exposure variable, and $LaggedCrime_{daily}$ represents the temporal lagged outcome to control for temporal autocorrelations. I also include a set of dummy indicators for each census tract to account for neighborhood-level fixed effects in this model.

To explore differences between weekdays and weekends in the longitudinal relationship between mobility and crime, I incorporate interaction terms between inward population flow and the binary weekend variable, as well as between outward population flow and that same indicator. I first add each interaction term to the regression model shown in equation (3) individually, then include all of them together. If any significant moderation effects appear, I also visualize those interaction effects using marginal effect interaction plots.

VI. Supplementary analysis and robustness check

I conduct several additional analyses as supplements for the purpose of robustness checks. First, in Appendix B, I replicate the analysis using negative binomial regression models and compare the results to assess the potential impacts of overdispersion. Second, I compare the primary results obtained using Poisson regression with MESF to those generated using Generalized Additive Modeling (GAM) as an alternative method, as shown in Appendix C. Third, I compare the outcomes for robbery and burglary with those derived from their respective subtypes, and summarize those results in Appendix D. I classify robbery incidents into three subtypes: 1) street robbery, 2) commercial robbery, and 3) carjacking. Similarly, I divide burglary incidents into two subtypes: 1) residential burglary and 2) non-residential burglary. Fourth, I compare the results of seasonal variations obtained from weekly data with those derived from monthly data, as presented in Appendix E. Finally, I compare the differences in panel regression outcomes when using a binary weekday/weekend indicator versus a categorical day-of-the-week indicator and show the results of the latter models in Appendix F.

Chapter 5: Mobility, Crime, and Their Connections in Baltimore

In this chapter, I examine collective mobility patterns, crime incidents, and their connections in Baltimore during 2019. Of fundamental interest here is whether a significant connection exists between indicators of collective mobility patterns and crime rates in Baltimore. Specifically, after accounting for spatial autocorrelation, I examine this relationship with and without including additional covariates and lagged measures. In the first section, I discuss the spatial distributions of collective mobility patterns and crime outcomes among Baltimore neighborhoods. In the second section, I compare patterns of residential mobility and dynamic population flow—both inward and outward— across neighborhoods grouped by different structural attributes and land use compositions. In the third section, I examine the relationship between each indicator of collective mobility patterns and the crime rates by including them separately and then simultaneously in the spatial regression models, without any additional variables. In the fourth section, I examine the relationship between collective mobility patterns and crime outcomes, with other covariates and lagged outcomes controlled in the models.

Spatial distributions of mobility and crime

Crime incidents were widespread and unevenly distributed across Baltimore neighborhoods in the pre-COVID era. In 2019, the city recorded nearly 350 homicides, approximately 5,000 robberies, and around 5,400 burglaries. **Figure 5.1** illustrates the trends in major crime types from 2014 to 2019. The total number of homicides in 2019 was near its five-year peak, similar to levels seen in 2017. However, both robbery and burglary incidents declined from their 2017 peak. The overall number of homicides remains significantly lower than that of robberies and burglaries, with minimal fluctuation over the years. Notably, the sharp decline in burglary incidents since 2017 led to robbery and burglary numbers becoming nearly equal in 2019.

Figure 5.1

Number of incidents for major crime types from 2014 to 2019

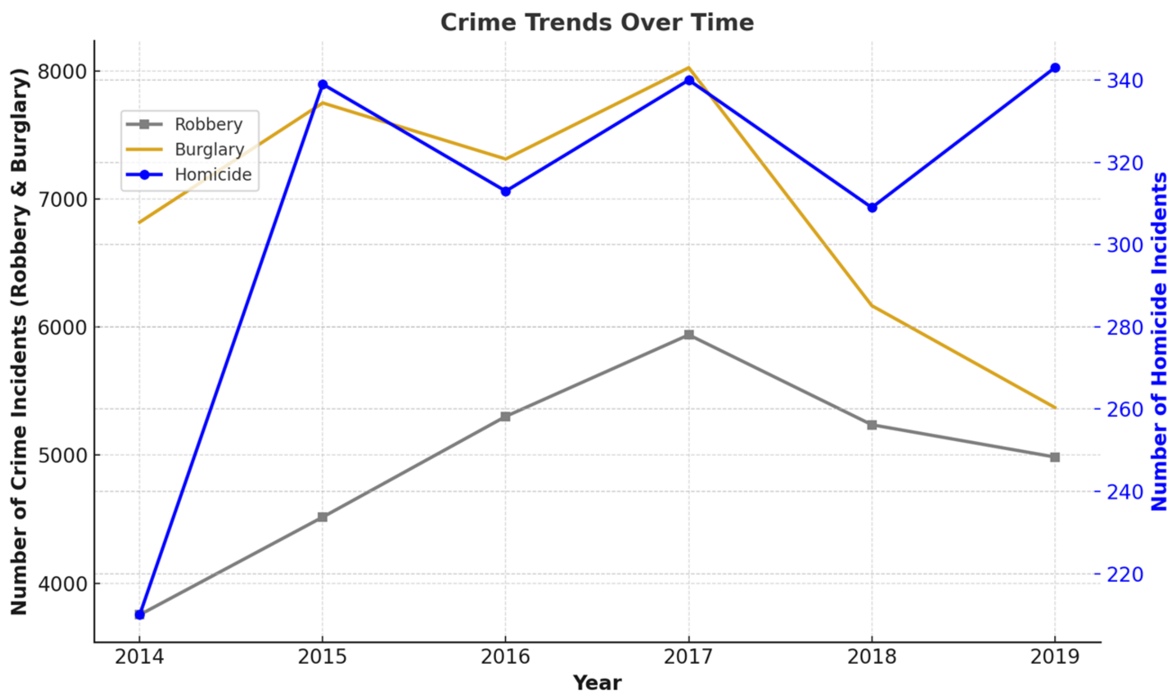


Figure 5.2 illustrates the spatial distribution of homicide incidents and corresponding rates (per 100,000 individuals) in Baltimore City for 2019. About 38% of the neighborhoods ($n = 75$) do not have any homicide incidents known to the police during 2019. The highest concentrations of homicides are found in the central and western areas, where several neighborhoods recorded five or more incidents. Some neighborhoods in the Southwest and Northwest also recorded moderately high homicide counts, while the outer regions—especially in the Northeast and Far South—reported few or no homicides. When adjusted for population, homicide rates remain high in the Central and Western Baltimore areas but also reveal smaller neighborhoods elsewhere with disproportionately high levels of homicide. Some Southern and

Northwestern neighborhoods, despite having low homicide counts, exhibit high homicide rates due to their smaller ambient population sizes. Overall, the Central and Western parts of Baltimore bear the greatest burden of homicides, both in absolute numbers and per capita rates.

Figure 5.2

Spatial distribution of homicide counts and rates in Baltimore City during 2019

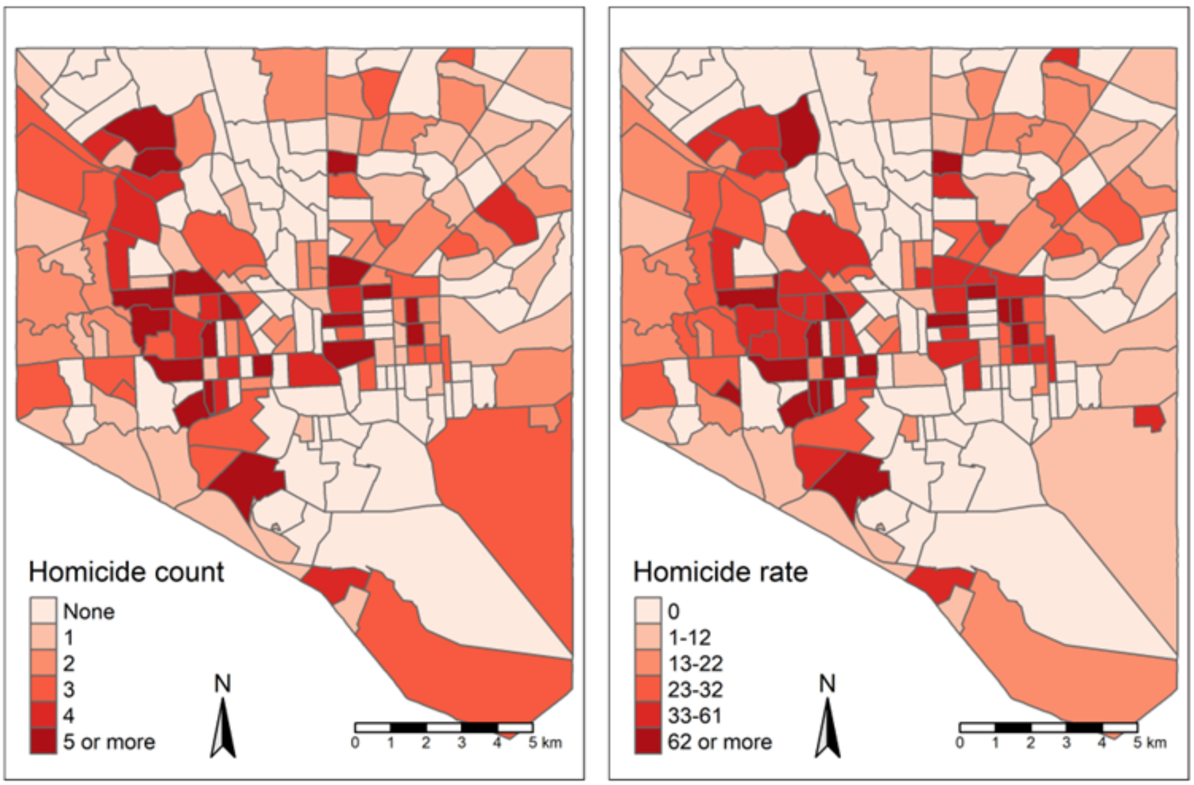


Figure 5.3 illustrates the spatial distribution of robbery incidents and rates (per 100,000) across Baltimore neighborhoods in 2019. Unlike the more localized homicide patterns in Figure 5.2, robberies are more widely distributed, extending into Northwestern and Southwestern areas. The highest concentrations (48 or more incidents) are found in Central and Western Baltimore, with additional hotspots in the Southwest and Northwest. Moderate robbery counts (20-47 incidents) spread outward into surrounding neighborhoods, while the outer regions, particularly

in the Northeast and Far South, report fewer incidents than other areas. When adjusted for population, robbery rates remain highest in Central and Western Baltimore but also highlight several smaller neighborhoods with disproportionately high robbery levels. While most areas on the periphery of the city have low robbery rates, some outer neighborhoods still experience moderate robbery levels.

Figure 5.3

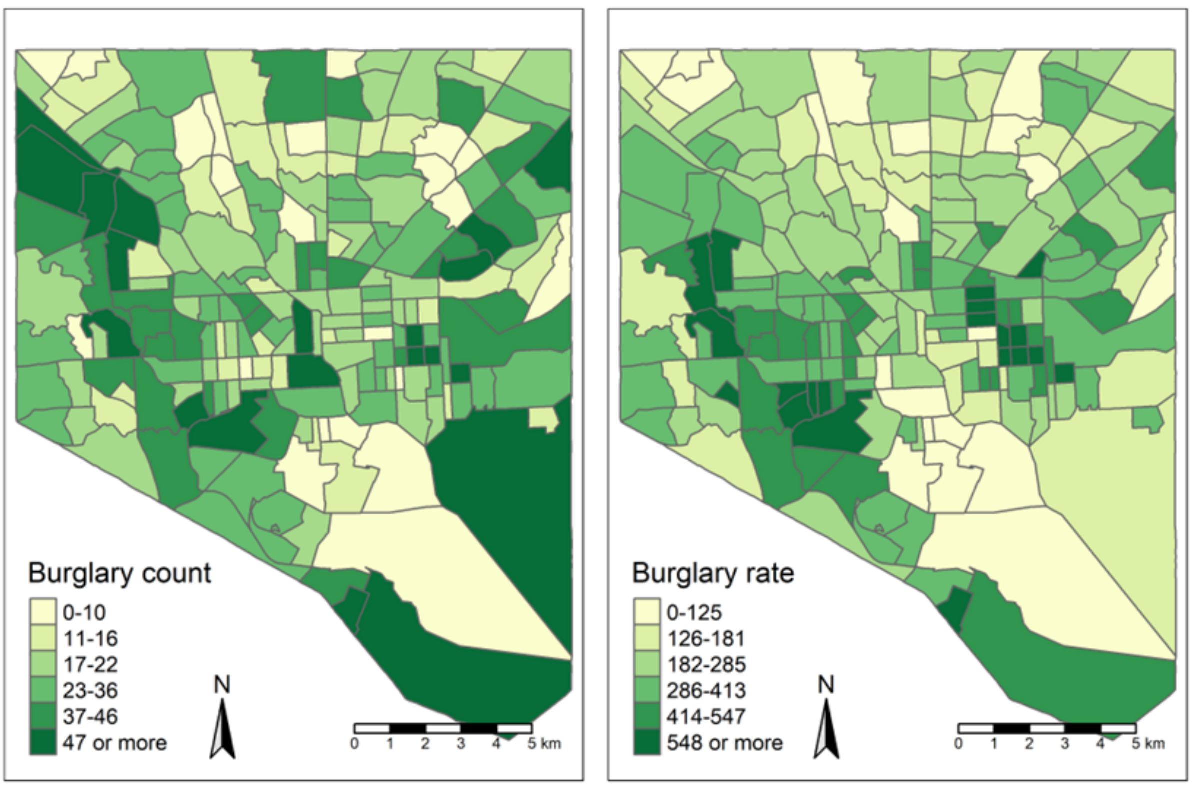
Spatial distribution of robbery counts and rates in Baltimore City during 2019

Figure 5.4 illustrates the spatial distribution of burglary incident counts and rates (per 100,000) across Baltimore neighborhoods in 2019. Compared to homicides and robberies, burglaries are more evenly distributed throughout the city. The highest burglary counts are concentrated in Central, Western, and Southern Baltimore, while moderate burglary counts (23-

46 incidents) are widespread, making burglary patterns less clustered than those of the two violent crimes. Outer regions, particularly in the Northeast and parts of the South, report few burglaries. When adjusted for population, burglary rates remain highest in the Western and Southern parts of the city, with a few additional high-rate neighborhoods in the East. In comparison, most outlying areas have low burglary rates, and some Southwestern outlying neighborhoods experience relatively high levels.

Figure 5.4

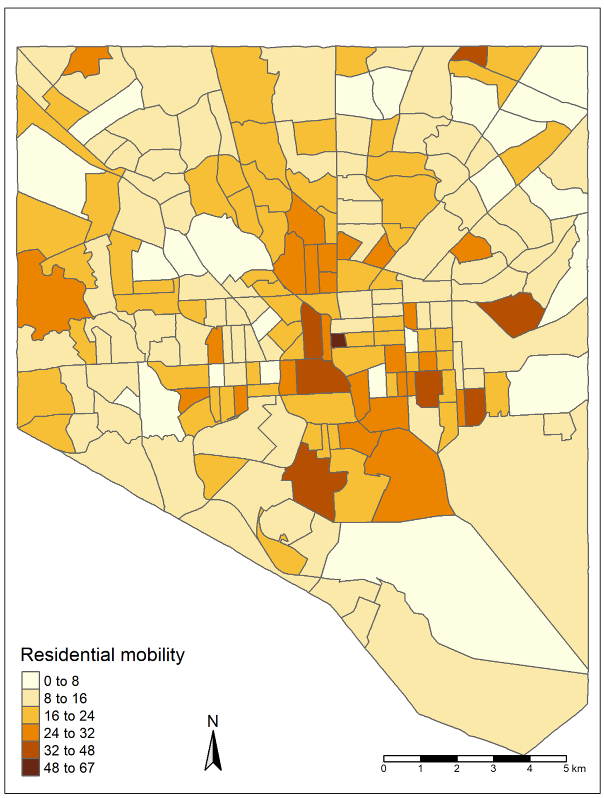
Spatial distribution of burglary counts and rates in Baltimore City during 2019



I also visualize the spatial variations of each indicator for collective mobility patterns. **Figure 5.5** shows the distribution of residential mobility in Baltimore neighborhoods during 2019. The highest turnover rates are concentrated in Central Baltimore, with additional high levels in parts of the Western and Southern areas. Many neighborhoods surrounding the city center and extending toward the northwest and eastern parts exhibit moderate mobility rates. The outermost regions, particularly in the Northeast and some Southwestern areas, show the lowest levels of residential mobility. The pattern of residential turnover in Baltimore also closely mirrors the description by Park and Burgess (1925). Nearly a century later, urban neighborhoods with high residential mobility still cluster near the city center, particularly within the central business districts and the surrounding transition zone.

Figure 5.5

Spatial variations of residential mobility in Baltimore City during 2019



In **Figure 5.6,** I visualize the spatial patterns of inward population flow across Baltimore neighborhoods in 2019. Central Baltimore attracts the most incoming visitors: the highest levels of inward population movement are concentrated in select areas, primarily among the central business district and certain locations along the inner harbor. Moderate inward flows are widespread in several Western and Southern neighborhoods. The low levels of inward movement are relatively common in the Northeastern, Southwestern, and some outer neighborhoods.

Figure 5.6

Spatial variations of inward population flow in Baltimore City during 2019

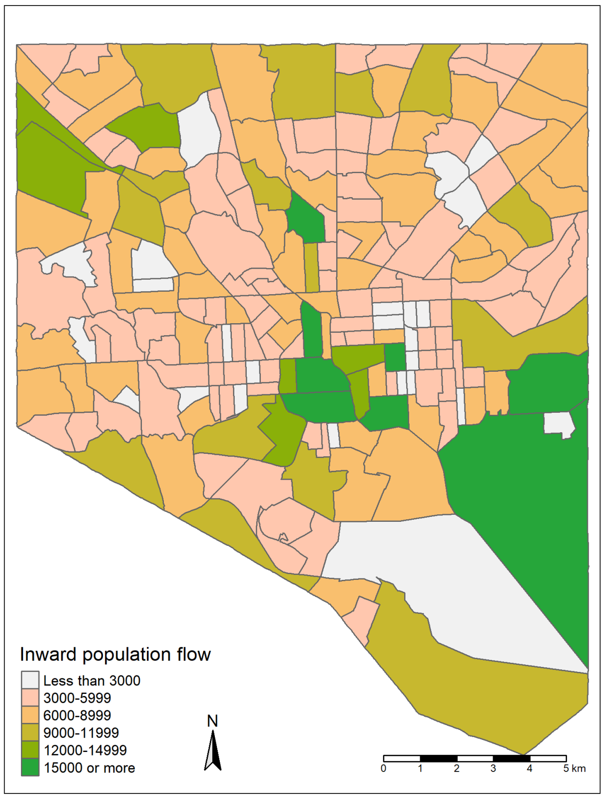
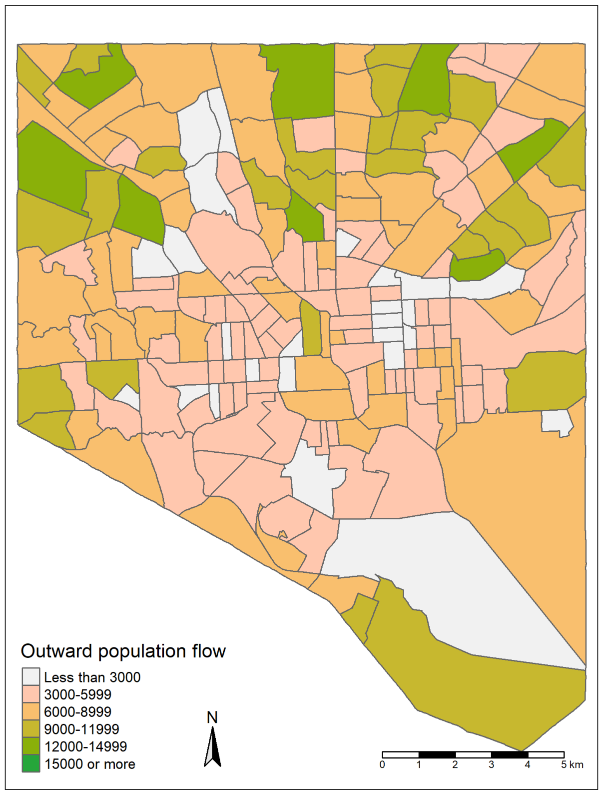


Figure 5.7 shows the spatial distribution of outward population flows across Baltimore neighborhoods in 2019. Compared to inward flows, outward movement is more common, with the highest levels concentrated in several neighborhoods in Southwestern and Northwestern Baltimore. Moderate outward flows are present across much of the city, including Central and

Western neighborhoods. In contrast, outward flow is relatively low in a few neighborhoods, primarily among those near the city's borders with neighboring counties.

Figure 5.7

Spatial variations of outward population flow in Baltimore City during 2019



Notably, there are distinct mismatches between inward and outward flows in some areas. Some Central neighborhoods experience high inward flows but do not exhibit equally high outward movement. Conversely, several neighborhoods in the Northwest and Southwest see high outward flows without a correspondingly high influx of visitors. Peripheral areas generally show balanced population dynamics, with both low inward and outward flows. Additionally, a visual comparison with residential mobility (Figure 5.5) suggests that inward and outward population flows (Figures 3B and 3C) align more closely with the spatial distribution of crime incidents in Baltimore, highlighting a potential relationship between mobility patterns and crime dynamics.

Collective mobility across different structural and land use conditions

Before proceeding to complex quantitative analyses examining the potential relationships between indicators of collective mobility patterns and crime rates in Baltimore, it is essential to conduct additional descriptive analyses. These preliminary analyses will help clarify how residential mobility, inward population flow, and outward mobility vary across neighborhoods with distinct demographic characteristics, structural features, and land use patterns—factors that will later be controlled for in regression models.

To show how indicators of collective mobility patterns vary across different levels of each structural characteristic, I use three quartile points (25%, 50%, 75%) and two decile points (10%, 90%) to categorize each covariate of structural characteristics into six groups (less than 10%, between 10% and 25%, between 25% and 50%, between 50% and 75%, between 75% and 90%, and over 90%). Then, I report each mobility indicator's corresponding means and standard deviations within each category for every feature.

I first examine the quantity of inward population flows across different structural features among Baltimore neighborhoods and summarize the results in **Table 5.1**. Several aspects of Table 5.1 are especially noteworthy. First, inward population flow generally declines as the levels of disadvantage and housing vacancy increase, with neighborhoods in the over 90% group for both features exhibiting the lowest quantity of individuals visiting them as destinations. Second, inward population movements become prevalent in neighborhoods with a high concentration of immigrants and renter-occupied housing units, as neighborhoods in the over 90% group for both features show the highest level of inward population flows. Third, inward

Table 5.1

Inward population flows by categories of structural characteristics (N=198)

Category	Disadvantage (Index)	Immigration Prevalence (Index)	African American (%)	Hispanic/Latino (%)	Young Male Aged 15-24 (%)	Housing Vacancy (%)	Renter-occupied Housing (%)
<=10%	7486.38 (5266.37)	4774.61 (2726.39)	6502.95 (3345.70)	4742.61 (2041.23)	6528.18 (5509.37)	7689.45 (4913.24)	5950.72 (2617.97)
10-25%	7787.01 (9395.94)	4822.78 (2167.16)	9980.10 (10277.77)	5483.73 (2852.24)	6931.16 (3922.33)	6042.31 (2946.22)	5324.74 (2725.01)
25-50%	7158.57 (3646.23)	6402.61 (3670.98)	6211.26 (3140.01)	5993.66 (2733.57)	6389.53 (3942.17)	7244.77 (4717.78)	6537.42 (4279.66)
50-75%	5675.18 (3911.71)	5821.61 (2945.07)	5673.36 (2887.82)	6018.68 (3273.63)	5293.31 (3019.08)	6943.44 (7286.97)	6172.45 (4054.20)
75-90%	5340.77 (2233.73)	6522.14 (4132.30)	5490.50 (2696.72)	8986.45 (9800.01)	7466.56 (9061.23)	5423.29 (2907.89)	5505.01 (3156.07)
>90%	4343.92 (2459.52)	11474.75 (11741.63)	4125.87 (1825.19)	7129.71 (6111.71)	6325.65 (3926.14)	3200.99 (1301.96)	9834.03 (11408.70)

Note. Standard deviations in parentheses.

population flows vary inconsistently across neighborhoods with different ethnoracial compositions. Neighborhoods within the group of 10-25% for the percentage of African American population have the highest level of inward population flow, while those belonging to the group of 90% and above show the lowest level. In contrast, neighborhoods in the category of 75-90% for Hispanic/Latino population coverage see the highest inflows, but present their lowest average values among neighborhoods in the less than 10% group.

I perform similar comparisons for outward population flow and summarize its relevant results in **Table 5.2**. While the average level of outward population flow shows similar patterns of change across some structural characteristics, it also exhibits distinct variation trends compared to inward population flow across categories of several other features. First, consistent with the patterns observed for inward population flow, outward population flow shows the lowest average values among neighborhoods within the group of over 90% and above for housing vacancy rates. Similarly, outward population flow remains lowest in the category of less than 10% for the immigration prevalence index, mirroring the trend seen in inward flows. The average level of outward population flow is also highest in neighborhoods within the 25-50% category of African American population percentage, similar to the pattern observed for inward flows. Second, though outward flow declines sharply in the highest disadvantage category (i.e., beyond the 90% group), it peaks in the moderate range, particularly within the 25-50% group. Third, in contrast to inward population flow—which reaches its highest level in the group beyond the 90% for renter-occupied housing—outward flow is highest among neighborhoods in the lowest category of this feature (i.e., less than 10% group). Besides, outward population flows show little variations across different categories of Hispanic/Latino population percentage and

Table 5.2

Outward population flows by categories of structural characteristics (N=198)

Category	Disadvantage (Index)	Immigration Prevalence (Index)	African American (%)	Hispanic/Latino (%)	Young Male Aged 15-24 (%)	Housing Vacancy (%)	Renter-occupied Housing (%)
<=10%	5494.13 (1846.93)	4656.57 (2298.47)	5357.02 (2020.09)	5239.80 (2867.41)	5263.67 (2385.38)	8464.04 (3673.93)	7603.58 (3422.21)
10-25%	5877.32 (3177.00)	5302.30 (2656.18)	6901.98 (3222.61)	6052.57 (2904.99)	5700.37 (2328.81)	6406.82 (2641.17)	6335.01 (2874.53)
25-50%	7897.25 (3041.86)	6535.56 (2977.70)	6019.18 (2742.31)	6886.14 (2966.23)	6547.25 (2842.21)	6643.50 (2972.72)	6553.34 (2671.76)
50-75%	5774.87 (2525.20)	6513.03 (2978.47)	6272.59 (3184.39)	5596.83 (2712.04)	6028.95 (3036.40)	5958.53 (2411.89)	5653.23 (2890.90)
75-90%	5207.99 (2513.42)	5738.76 (2534.04)	5788.85 (2441.69)	5888.06 (2916.93)	6256.07 (2996.06)	5011.38 (2106.74)	5066.87 (2456.13)
>90%	4125.47 (1498.42)	6673.77 (3116.60)	5360.05 (2971.88)	6158.66 (2652.77)	5864.43 (3488.41)	3445.96 (1303.38)	5372.90 (2637.11)

Note. Standard deviations in parentheses.

young males aged 15–24. This contrasts with the more substantial group differences observed for these features in inward population flow.

Next, I compare the percentage difference in residential mobility measures across different categories of each structural feature and summarize the results in **Table 5.3**. I find several similarities and inconsistencies compared to the prior findings for inward and outward population flows. First, similar to the pattern observed for both inward and outward population flows, the level of residential mobility generally decreases as the level of disadvantage increases, with the neighborhoods among the highest disadvantage category (i.e., beyond the 90% group) having the lowest average level of residential turnover. Similar to the patterns observed in inward and outward population flows, neighborhoods within the lowest category of immigration prevalence index (i.e., less than 10% group) exhibit the lowest level of residential mobility. Second, similar to the patterns only observed for inward population flow, neighborhoods within the highest category of renter-occupied housing coverage (i.e., beyond the 90% group) also have the highest levels of residential mobility on average. Another finding that parallels the inward population flow is that neighborhoods in the category of 75-90% for Hispanic/Latino population percentage show the highest level of residential mobility, and present its lowest percentages among neighborhoods in the less than 10% group. Third, similar to outward population flow, residential mobility exhibits minimal variations across the different categories of the proportion indicator for the young male populations aged 15–24. In addition, different from the findings for both inward and outward population flows, neighborhoods with the 25-50% category of housing vacancy rates present the highest level of residential mobility. Residential mobility is also more prevalent among neighborhoods in the lowest category of African American population percentage (i.e., less than 10%).

Table 5.3

Residential mobility (percentage) by categories of structural characteristics (N=198)

Category	Disadvantage (Index)	Immigration Prevalence (Index)	African American (%)	Hispanic/Latino (%)	Young Male Aged 15-24 (%)	Housing Vacancy (%)	Renter-occupied Housing (%)
<=10%	23.24 (7.14)	11.52 (6.14)	23.92 (6.51)	12.57 (5.61)	18.26 (7.98)	16.86 (8.12)	12.15 (6.46)
10-25%	20.18 (7.83)	15.33 (6.43)	20.26 (8.42)	12.91 (5.85)	18.27 (8.15)	15.37 (6.27)	15.58 (7.66)
25-50%	15.23 (7.05)	15.33 (6.96)	16.04 (7.27)	15.85 (7.31)	16.89 (7.77)	18.27 (8.75)	16.77 (5.95)
50-75%	14.22 (7.90)	15.57 (6.72)	14.59 (6.08)	17.38 (7.97)	14.14 (6.63)	16.06 (7.64)	15.57 (7.27)
75-90%	15.08 (5.71)	19.90 (8.00)	12.16 (4.67)	20.11 (8.33)	16.16 (8.64)	14.06 (6.40)	16.46 (7.27)
>90%	13.56 (6.17)	21.52 (10.22)	14.24 (9.07)	17.80 (8.14)	15.68 (6.88)	16.30 (7.98)	22.13 (11.32)

Note. Standard deviations in parentheses.

I also compare the level of three mobility indicators across neighborhoods with different land use patterns and summarize the relevant results in **Table 5.4**. Given the various types of land use purposes that exist within Baltimore City, I use their percentage indicators and re-classify all Baltimore neighborhoods into three types for simplicity: 1) residential majority ($n = 127$), with more than 50% of the land within the neighborhood used for residential purposes; 2) nonresidential majority ($n = 24$), with more than 50% of neighborhood land designated for nonresidential purposes (i.e., retail, industry, institutional, transportation, or other purposes); 3) multiple/mixed land use ($n = 47$), with none of the land use types constituting more than 50% of neighborhood land. I find that the average volume of inward population flow is much higher in nonresidential-majority and mixed land-use neighborhoods than in residential-majority neighborhoods, with little difference observed between the former two neighborhood types for this measure. Residential-majority neighborhoods exhibit a higher outward population flow than nonresidential-majority neighborhoods. However, the level of outward activity does not differ much between residential-majority and mixed land-use neighborhoods. Additionally, the average level of residential mobility is similar across all three types of neighborhoods.

Table 5.4

Collective mobility patterns by categories/types of land use (N=198)

Category/Type	**Inward Population Flow**	**Outward Population Flow**	**Residential Mobility (%)**
Residential majority (> 50%)	4996.64	6250.88	15.56
	(2134.18)	(2845.11)	(6.86)
Nonresidential majority (> 50%)	8571.46	5225.40	19.11
	(10110.48)	(2604.05)	(9.82)
Multiple/Mixed Land Use	8936.35	5950.35	16.91
	(5462.89)	(3016.56)	(8.36)

Note. Standard deviations in parentheses.

In general, the descriptive results in this section provide strong evidence that local neighborhood environments are closely linked to variations in collective mobility patterns. A few key findings stand out. First, across the various categories of disadvantage and immigration prevalence indices, all three mobility measures—residential mobility, inward flow, and outward flow—exhibit consistent trends. Highly disadvantaged neighborhoods seem to show low levels of collective mobility, while areas with high immigration concentrations experience significantly higher residential turnover and population movement levels than other parts of Baltimore. Second, when examining other structural features, such as the proportion of renter-occupied housing units and housing vacancy rates, similarities and discrepancies appear when comparing the three mobility indicators. Third, distinct patterns are evident across neighborhoods with different land use patterns: inward flows vary substantially, outward flows vary to a lesser degree, and residential mobility remains relatively stable across neighborhood types. Together, these findings underscore the importance of neighborhood-level structural, demographic, and local land use contexts in shaping collective mobility patterns.

<u>*Unadjusted mobility-crime relationship*</u>

Next, I analyze the bivariate relationships between mobility-related factors and crime outcomes using Pearson correlation coefficients, summarized in **Table 5.5**. To ensure consistency, I use crime rates (i.e., $CrimeRate_i = (\frac{CrimeCount_i}{AmbientPop_i}) \times 100{,}000$) instead of raw counts. For homicide rates, inward ($r(198) = -0.20$, $p = .006$) and outward population flows ($r(198) = -0.20$, $p = .005$) show significant negative correlations, while residential mobility, though also negative, is not statistically significant ($r(198) = -0.12$, $p = .082$). Regarding robbery rates, neither inward population flow ($r(198) = -0.06$, $p = .431$) nor residential mobility ($r(198) =

0.08, p = .280) show significant correlations, but outward flow exhibits a significant negative correlation (r(198) = -0.32, p < .001). For burglary rates, both inward (r(198) = -0.30, p < .001) and outward flows (r(198) = -0.23, p = .001) have significant negative correlations, whereas residential mobility remains non-significant (r(198) = -0.06, p = .436). In general, the Pearson bivariate results indicate that when spatial autocorrelation or covariates are not accounted for, Hypothesis 1a is largely unsupported due to the insignificant correlation coefficients for residential mobility. Conversely, Hypothesis 1b is mostly supported by the significant negative correlations observed for most crime types, with the exception of the negative but statistically insignificant relationship between inward population flow and robbery rates.

Table 5.5

Pearson correlation results for mobility-crime relationships

Variables[a]	**Homicide**	**Robbery**	**Burglary**
Residential mobility	-.12[+]	.08	-.06
Inward population flow	-.20**	-.06	-.30***
Outward population flow	-.20**	-.32***	-.23**
Number of observations	198	198	198

Note. r values represent Pearson correlation coefficients.
[a] Crime rates are used instead of raw counts.
[+] $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

I also conduct bivariate Poisson regression models that control only for spatial autocorrelation. Then, to examine unadjusted relationships, I include all three mobility-related factors while excluding other covariates or lagged measures. **Table 5.6** presents both the bivariate and unadjusted Poisson regression results for homicide rates. Residential mobility does not show a statistically significant relationship with homicide rates in either the bivariate (Model 1) or unadjusted model (Model 4), though both are negative. Outward population flow demonstrates the strongest and most consistent negative relationship with homicide rates: both the bivariate (Model 3) and unadjusted (Model 4) models indicate a significant negative association. Inward population flow also exhibits a negative relationship with homicide rates. In the bivariate model (Model 2), this association is significant, but when additional mobility indicators are included in Model 4, the effect size decreases, and the significance level drops to marginal significance $p < .10$).

Table 5.6

Bivariate and unadjusted Poisson regression for mobility and homicide rates in Baltimore

Variables[a]	**(1)**	**(2)**	**(3)**	**(4)**
Residential mobility	-0.21 (0.16)			-0.15 (0.14)
Inward population flow		-0.33* (0.14)		-0.21^{+} (0.12)
Outward population flow			-0.27*** (0.07)	-0.22** (0.07)
Number of observations	198	198	198	198

Note. $^{+}p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Clustered-robust standard errors in parenthesis.
[a] Baseline intercept and selected eigenvectors are not shown in the table.

For robbery rates, I follow the same process, with results presented in **Table 5.7**. Residential mobility is positively linked with robbery rates in the bivariate regression model (Model 1), but this positive association becomes insignificant when other mobility variables are included (Model 4). Inward population flow is positively linked with robbery rates: Model 2 (the bivariate model) shows a marginally significant positive relationship, but Model 4 (after including other mobility indicators) shows an increased effect size and a statistically significant association. Hence, it can be inferred that higher inward population flow is associated with higher robbery rates even when other mobility measures are taken into account. Outward population flow is the strongest and most consistent predictor of lower robbery rates, with both the bivariate (Model 3) and the unadjusted (Model 4) models showing a significant negative association between outward mobility and robbery rates.

Table 5.7

Bivariate and unadjusted Poisson regression for mobility and robbery rates in Baltimore

Variables[a]	**(1)**	**(2)**	**(3)**	**(4)**
Residential mobility	0.09* (0.04)			-0.04 (0.05)
Inward population flow		0.05^{+} (0.03)		0.07** (0.02)
Outward population flow			-0.22*** (0.05)	-0.25*** (0.05)
Number of observations	198	198	198	198

Note. $^{+}p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Clustered-robust standard errors in parenthesis.
[a] Baseline intercept and selected eigenvectors are not shown in the table.

Table 5.8 summarizes the bivariate and unadjusted Poisson regression results on the relationship between collective mobility patterns and burglary rates in Baltimore during 2019. Residential mobility has no significant association with burglary rates in either the bivariate (Model 1) or unadjusted model (Model 4). Inward population flow shows a marginally significant negative relationship with burglary rates in both the bivariate (Model 2) and unadjusted model (Model 4), indicating a weak association between increased inward mobility and lower burglary rates. Outward population flow is the strongest predictor, with a consistent and highly significant negative relationship across both the bivariate (Model 3) and unadjusted models (Model 4), showing that neighborhoods with greater outward mobility experience lower burglary rates.

Table 5.8

Bivariate and unadjusted Poisson regression for mobility and burglary rates in Baltimore

Variables[a]	**(1)**	**(2)**	**(3)**	**(4)**
Residential mobility	-0.08 (0.06)			-0.02 (0.05)
Inward population flow		-0.15^{+} (0.07)		-0.12^{+} (0.07)
Outward population flow			-0.11*** (0.03)	-0.08*** (0.02)
Number of observations	198	198	198	198

Note. $^{+}p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Clustered-robust standard errors in parenthesis.
[a] Baseline intercept and selected eigenvectors are not shown in the table.

<u>*Adjusted mobility-crime relationship*</u>

In this section, I continue to examine the adjusted relationships between mobility-related factors and crime rates while controlling for all identified confounders in the spatial regression model. A complete list of adjusted regression results, including all predictors and covariates used in the analysis, is provided in Appendix A for reference. **Table 5.9** presents the regression results of the effects of residential mobility, inward population flow, and outward population flow on homicide rates while controlling for structural characteristics, land use factors, and lagged homicide counts. Model 1 shows that residential mobility has a marginally significant positive relationship with homicide rates. Following Model 2 and Model 3, the effect size declines and is no longer significant. Inward population flow is negatively related to homicide rates in all models, but the relationship is not statistically significant. Though the effect size is slightly positive in Models 2 and 3 after including land use patterns and the lagged outcome, respectively, it fails to achieve statistical significance. Outward population flow initially has a small positive, but not statistically significant, association with homicide rates. Once the lagged outcome is incorporated, the coefficient becomes negative but remains statistically insignificant.

Table 5.9

Adjusted regression results for mobility and homicide rates in Baltimore during 2019

Variables[ab]	**(1)**	**(2)**	**(3)**
Residential mobility	0.17^{+} (0.10)	0.14 (0.11)	0.14 (0.10)
Inward population flow	-0.01 (0.06)	-0.04 (0.05)	-0.05 (0.05)
Outward population flow	0.02 (0.06)	0.02 (0.08)	-0.05 (0.07)
Structural characteristics	Yes	Yes	Yes
Land use patterns	No	Yes	Yes
Lagged outcome	No	No	Yes
Number of observations	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.
[a] Baseline intercept and selected eigenvectors are not shown in the table.
[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

Compared to the bivariate and unadjusted regression results for homicide rates in Table 5.6, the findings reveal notable differences. When only mobility factors are considered, residential mobility has a negative but non-significant association with homicide rates (Table 5.5, Models 1 & 4). However, once structural characteristics are included, this relationship reverses, becoming a marginally significant positive effect (Table 5.9, Model 1), though it weakens and loses significance as additional controls are introduced (Table 5.9, Models 2 & 3). The initial analysis presents a statistically significant (Table 5.6, Model 2) or marginally significant (Table 5.6, Model 4) negative relationship between inward population flow and homicide rates. After controlling for structural and other contextual factors, this association becomes non-significant.

Outward population flow exhibits a negative relationship with homicide rates in both the bivariate (Table 5.6, Model 3) and the unadjusted regression results (Table 5.6, Model 4). However, when structural characteristics, land use, and the lagged outcome are added to the model, this relationship also declines and loses statistical significance. Overall, after accounting for confounding variables, the previously observed associations between mobility variables and homicide rates diminish substantially and lose statistical significance.

Table 5.10

Adjusted regression results for mobility and robbery rates in Baltimore during 2019

Variables[ab]	**(1)**	**(2)**	**(3)**
Residential mobility	0.03 (0.05)	-0.01 (0.05)	0.001 (0.03)
Inward population flow	0.05 (0.03)	-0.04 (0.04)	-0.37*** (0.08)
Outward population flow	-0.14*** (0.03)	-0.10** (0.04)	-0.05 (0.04)
Structural characteristics	Yes	Yes	Yes
Land use patterns	No	Yes	Yes
Lagged outcome	No	No	Yes
Number of observations	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.
[a] Baseline intercept and selected eigenvectors are not shown in the table.
[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

Table 5.10 presents adjusted regression results examining the relationship between collective mobility patterns and robbery rates while progressively accounting for structural characteristics, land use patterns, and the lagged outcome. Across all models, residential mobility does not exhibit a statistically significant association with robbery rates. Initially, inward population flow shows a positive but non-significant association with robbery rates in Model 1. After adjusting for land use patterns in Model 2, the coefficient turns negative but remains non-significant. However, once the lagged outcome is included in Model 3, the relationship becomes strongly negative and highly significant. This finding indicates that when other variables are held constant, with an increase of approximately 5,000 individuals visiting a neighborhood, the natural log of the expected robbery rate decreases by 0.37 units, corresponding to an approximate 31% reduction in robbery rates. For outward population flow, Models 1 and 2 show a significant negative association with robbery rates, suggesting that high outward mobility is linked to low robbery rates. However, after accounting for the lagged outcome in Model 3, this effect declines considerably and loses statistical significance.

The comparison between the bivariate and unadjusted regression results in Table 5.7 and the adjusted regression models in Table 5.10 reveals notable shifts in the relationships between mobility factors and robbery rates after accounting for additional covariates. The association between residential mobility and robbery rates remains largely insignificant once other mobility factors (Model 4, Table 5.7) and additional covariates are included in the models (Model 1-3, Table 5.10). Inward population flow, which initially shows a positive association with robbery rates in the unadjusted models (Model 4, Table 5.7), undergoes a substantial shift, becoming significantly negative once the lagged outcome is introduced in the adjusted models (Model 3, Table 5.10). Outward population flow, which is strongly and significantly negatively associated with robbery rates in the bivariate (Model 3, Table 5.7) and unadjusted models (Model 4, Table 5.7), retains its statistical significance in the first two adjusted models (Models 1 & 2, Table 5.10). However, once prior robbery rates are accounted for in the final model (Model 3, Table 5.10), the effect weakens and loses significance.

Table 5.11 presents the adjusted regression results for the relationship between collective mobility patterns and burglary rates. Residential mobility initially shows a significant positive association with burglary rates in Model 1. After accounting for land use patterns and the lagged outcome in Model 3, the effect weakens but remains statistically significant. A one-unit increase, reflecting an 8.5 percentage point rise in the population that changed residence in the past five years, corresponds to a 0.08-unit increase in the natural log of the expected burglary rate, equivalent to an 8.3% increase in burglary rates.

Table 5.11

Adjusted regression results for mobility and burglary rates in Baltimore during 2019

Variables[ab]	**(1)**	**(2)**	**(3)**
Residential mobility	0.11* (0.05)	0.07 (0.04)	0.08** (0.03)
Inward population flow	-0.10 (0.07)	-0.11* (0.04)	-0.14*** (0.03)
Outward population flow	0.04 (0.03)	0.03 (0.03)	-0.15** (0.06)
Structural characteristics	Yes	Yes	Yes
Land use patterns	No	Yes	Yes
Lagge outcome	No	No	Yes
Number of observations	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.
[a] Baseline intercept and selected eigenvectors are not shown in the table.
[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

Inward population flow starts with a negative but non-significant association with burglary rates in Model 1. After adjusting for land use patterns in Model 2, the relationship becomes significant, and in Model 3, the negative effect strengthens further after controlling for the lagged outcome. An influx of 5,000 additional individuals into a neighborhood is associated with a 0.14-unit decrease in the natural log of the expected burglary rate, corresponding to a 13.1% reduction in burglary rates. Outward population flow is not significantly associated with burglary rates in Models 1 and 2. However, in Model 3, after accounting for past burglary rates, the effect becomes significantly negative. This suggests that after considering prior burglary levels, 2,900 additional individuals leaving a neighborhood corresponds to a 0.15-unit decrease in the natural log of the expected burglary rate, or a 13.9% reduction in burglary rates.

Compared to the bivariate and unadjusted regression results in Table 5.8, the adjusted models in Table 5.11 reveal notable shifts in these relationships. In the unadjusted models (Models 1 and 4, Table 5.8), residential mobility has no significant association with burglary rates. However, in the adjusted models, the relationship becomes positive and statistically significant in Models 1 and 3, suggesting that when structural and prior crime factors are accounted for, higher residential mobility is linked to increased burglary rates. For inward population flow, the unadjusted models (Models 2 and 4, Table 5.8) indicate a marginally significant negative association with burglary rates. In the adjusted models (Models 2 and 3, Table 5.11), this relationship strengthens and becomes highly significant, particularly after controlling for land use and prior burglary rates. This suggests that the earlier models underestimated the strength of this effect and that higher inward mobility is consistently associated with lower burglary rates. Outward population flow, which showed no significant association with burglary rates in the unadjusted models (Models 3 and 4, Table 5.8), becomes significantly negative in the fully adjusted model (Model 3, Table 5.11). The lack of significance in the unadjusted models suggests that the relationship between outward flows and burglary rates is obscured by confounding variables, which the adjusted models reveal more clearly.

Within the final adjusted model (Model 3, Table 5.11), residential mobility remains positively and significantly associated with burglary rates, while both inward and outward population flows show significant negative associations, demonstrating their role in reducing burglary rates after accounting for confounding factors.

Summary

Finally, I connect my findings to the hypotheses outlined in the previous chapter. Hypothesis 1a predicts that *higher residential mobility is associated with higher crime rates*. This hypothesis is partially supported, as the relationship between residential mobility and crime varies by offense type. In most models, residential mobility does not show a significant association with homicide or robbery rates. However, for burglary, it has a significant positive relationship in the adjusted models, particularly after controlling for land use and prior burglary rates.

Hypothesis 1b suggests that *higher population flows (both inward and outward) are associated with lower crime rates*, which is partially supported. Inward population flow is significantly negatively associated with robbery rates, and both inward and outward flows show significant negative correlations with burglary rates. However, neither type of mobility flow has a significant relationship with homicide rates, indicating that the effect of population flows on crime is crime-specific.

Hypothesis 1c predicts that *inward population flow will be associated with larger decreases in robbery rates than burglary rates.* This hypothesis is partially supported, as inward population flow shows a stronger negative association with robbery than with burglary rates only in the final adjusted model, not across all models.

Also, hypothesis 1d states that *outward population flow will be associated with larger decreases in burglary rates than robbery rates*. This hypothesis is partially supported, as outward population flow has a stronger and more consistent negative relationship with burglary rates. However, it also initially influences robbery rates, though this effect weakens after adjusting for prior crime levels.

Overall, these findings underscore the complex relationship between collective mobility and crime, demonstrating that the effects of collective mobility patterns vary based on crime type, mobility measure, and model specifications. Building on these insights, the next chapter explores the spatial variations within these mobility-crime relationships to examine how their effects may differ across neighborhoods with various intensities of police activities.

Chapter 6: Spatial Variations within the Mobility-Crime Connections

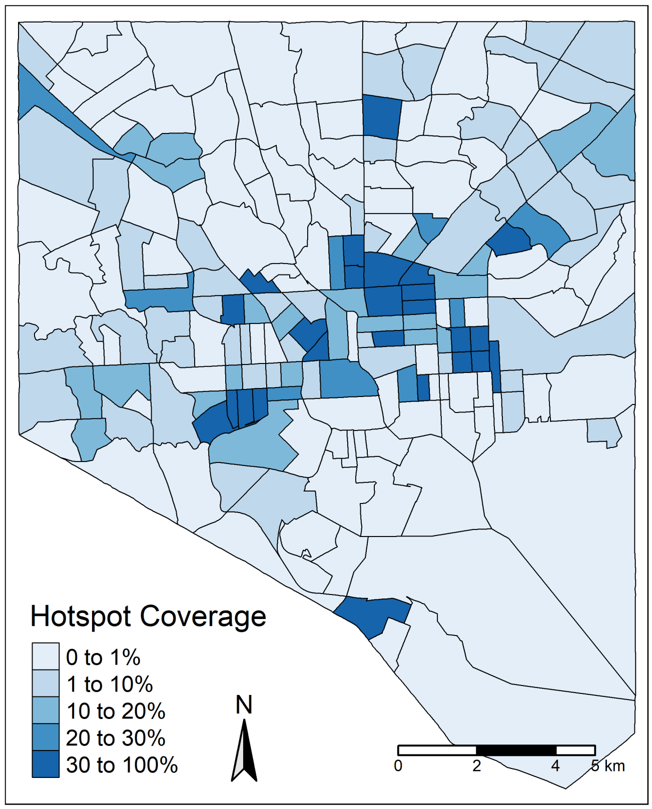
In this chapter, I explore the potential spatial variations in the relationship between collective mobility patterns and crime incidents in Baltimore during 2019. My primary focus is to investigate whether there is local heterogeneity in the impact of three mobility-related factors on crime incidents in different neighborhoods. I examine whether this heterogeneity is due to the varying intensity of police patrol activities across the city. In the first section, I assess the spatial distribution of police patrol activities/BPD crime hotspots across Baltimore neighborhoods. The second section examines the moderating role of police patrol intensity/neighborhood hotspot coverage on the relationship between collective mobility patterns and crime incidents, employing Poisson regression with MESF and interaction terms.

Police patrol activity and crime hotspot coverage in Baltimore

Regarding the intensity of police patrol activity, I use the distribution of crime hotspots as the proxy indicator. **Figure 6.1** presents the spatial distribution of the percentage of BPD crime hotspots within each Baltimore neighborhood during 2019. Approximately 32% ($n = 64$) of Baltimore's neighborhoods did not contain any areas identified as BPD crime hotspots. Other than those neighborhoods without any coverage of BPD crime hotspots, multiple neighborhoods had less than 10% of lands identified as BPD crime hotspots, and a small number of neighborhoods had that number ranging from 10 to 30 percent. However, in twenty-five neighborhoods (census tracts), over 30% of the land area fell within BPD-identified crime hotspots, with the majority of these neighborhoods located near Central Baltimore. Although these neighborhoods constitute less than 5% of Baltimore's total land area, they account for approximately 22.74% of all homicides, 16.61% of all robberies, and 15.92% of all burglaries in Baltimore in 2019.

Figure 6.1

Spatial distribution of BPD crime hotspot coverage in Baltimore City during 2019



Note. This figure shows the uneven level of police patrol activities across Baltimore neighborhoods, using each neighborhood's BPD crime hotspot coverage as a proxy.

<u>*The moderating role of police patrol activity intensity/crime hotspot coverage*</u>

To further examine the potential moderating role of police patrol activity between mobility factors and crime rates, I incorporate interaction terms between residential mobility and police activity intensity, inward population flow and police activity intensity, and outward population flow and police activity intensity—both individually and simultaneously—into the Poisson regression models used in the previous chapter.

Table 6.1

Moderation analysis for collective mobility and homicide rates in Baltimore during 2019

Variables[abc]	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Inward population flow	-0.03	-0.03	-0.05	-0.03	-0.04	-0.05	-0.04
	(0.08)	(0.05)	(0.06)	(0.09)	(0.08)	(0.06)	(0.09)
Outward population flow	0.02	0.03	0.03	0.02	0.02	0.03	0.02
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Residential mobility	0.12	0.11	0.10	0.11	0.10	0.10	0.10
	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)	(0.13)
Police activity intensity	0.07	0.07	0.05	0.07	0.05	0.06	0.05
	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)
IPF*PAI	-0.01			-0.01	-0.01		-0.02
	(0.08)			(0.09)	(0.07)		(0.09)
OPF*PAI		0.01		0.01		0.02	0.02
		(0.04)		(0.06)		(0.04)	(0.06)
RM*PAI			0.07		0.07	0.07	0.07
			(0.04)		(0.05)	(0.05)	(0.05)
Structural characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Land use information	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Selected eigenvectors	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	198	198	198	198	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.

[a] Baseline intercept, selected eigenvectors, and covariates are not shown in the table.

[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

[c] Lagged outcome is excluded, RM=Residential mobility, IPF=Inward population flow, OPF =Outward population flow, PAI =Police activity intensity

Table 6.2

Moderation analysis for collective mobility and robbery rates in Baltimore during 2019

Variables[abc]	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Inward population flow	-0.09^{+}	-0.04	-0.05	-0.09^{+}	-0.10*	-0.06^{+}	-0.10^{+}
	(0.05)	(0.04)	(0.03)	(0.05)	(0.05)	(0.03)	(0.05)
Outward population flow	-0.05+	-0.07*	-0.08*	-0.04^{+}	-0.04	-0.06	-0.04
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)
Residential mobility	-0.06	-0.06	-0.05	-0.07	-0.07	-0.07	-0.07
	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Police activity intensity	0.20***	0.20***	0.16***	0.21***	0.18***	0.18***	0.19***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
IPF*PAI	0.06^{+}			0.05	0.06		0.04
	(0.04)			(0.04)	(0.04)		(0.04)
OPF*PAI		0.06^{+}		0.04		0.08*	0.05^{+}
		(0.03)		(0.03)		(0.04)	(0.03)
RM*PAI			0.05*		0.04	0.06**	0.05*
			(0.02)		(0.02)	(0.02)	(0.02)
Structural characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Land use information	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Selected eigenvectors	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	198	198	198	198	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.

[a] Baseline intercept, selected eigenvectors, and covariates are not shown in the table.

[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

[c] Lagged outcome is excluded, RM=Residential mobility, IPF=Inward population flow, OPF =Outward population flow, PAI =Police activity intensity

Table 6.1 presents the moderation analysis examining the interaction between collective mobility patterns and BPD crime hotspot coverage on the expected homicide rate. Contrary to my expectation, those results indicate that police patrol intensity does not significantly moderate the relationship between any of the three mobility factors, regardless of whether the interaction terms are included individually or together. Besides, the association between police activity intensity and homicide rates is positive, although not statistically significant.

Table 6.2 explores whether police activity intensity moderates the relationships between residential mobility, inward population flow, and outward population flow with robbery rates. Police activity intensity shows a significant positive association with robbery rates. Police patrol intensity significantly moderates the effect of outward population flow on robbery rates, as evidenced by a marginally significant, positive interaction in Model 2 that becomes statistically significant in Model 6. Similarly, police activity intensity moderates the relationship between residential mobility and robbery rates, with statistically significant, positive interactions observed in Models 3, 6, and 7. In contrast, for inward population flow, the interaction term is marginally significant and positive in Model 1 but loses significance in later models.

Figure 6.2 illustrates the moderating effect of police activity intensity on the relationship between outward population flow and robbery incidents in Baltimore during 2019. In neighborhoods with low police patrol intensity, where less than 10 percent of the land is classified as BPD crime hotspots (represented by the red and blue lines), outward population flow has a minimal and negative impact on robbery rates. As police activity intensity increases, the slope of the lines steepens, indicating that the moderating effect of police patrols becomes stronger with higher levels of enforcement. In high-policed neighborhoods, where 60 percent or more of the land is classified as BPD crime hotspots (represented by the orange and yellow lines), the relationship between outward population flow and robbery rates shifts from negative to positive. This suggests that in areas with intensive police patrols, predicted robbery rates rise sharply as outward population flow increases.

Figure 6.2

The interaction of outward population flow and police activity toward robbery in Baltimore

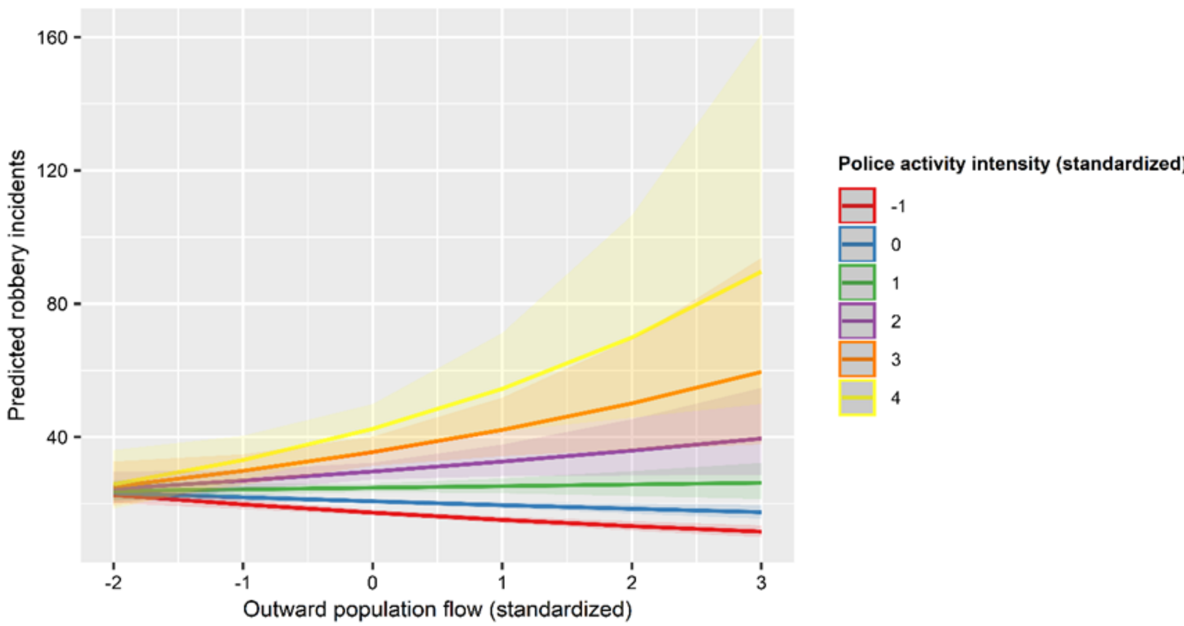


Figure 6.3 illustrates how police activity intensity moderates the relationship between residential mobility and predicted robbery incidents. In neighborhoods with low police activity (represented by the red and blue lines), residential mobility has little to no impact on robbery rates and may even have a slight negative effect. Like the pattern observed in Figure 6.2, the slopes of the lines become steeper as police activity intensity increases, indicating that the moderating effect of police presence strengthens with higher patrol intensity. At higher levels of police activity intensity (represented by the orange and yellow lines), the relationship becomes positive, indicating that in neighborhoods with intensive police patrols, robbery rates increase

significantly as residential mobility rises. This effect is especially pronounced in neighborhoods with the highest police activity intensity (yellow line), where robbery rates escalate sharply with greater residential mobility.

Figure 6.3

The interaction of residential mobility and police activity towards robbery in Baltimore

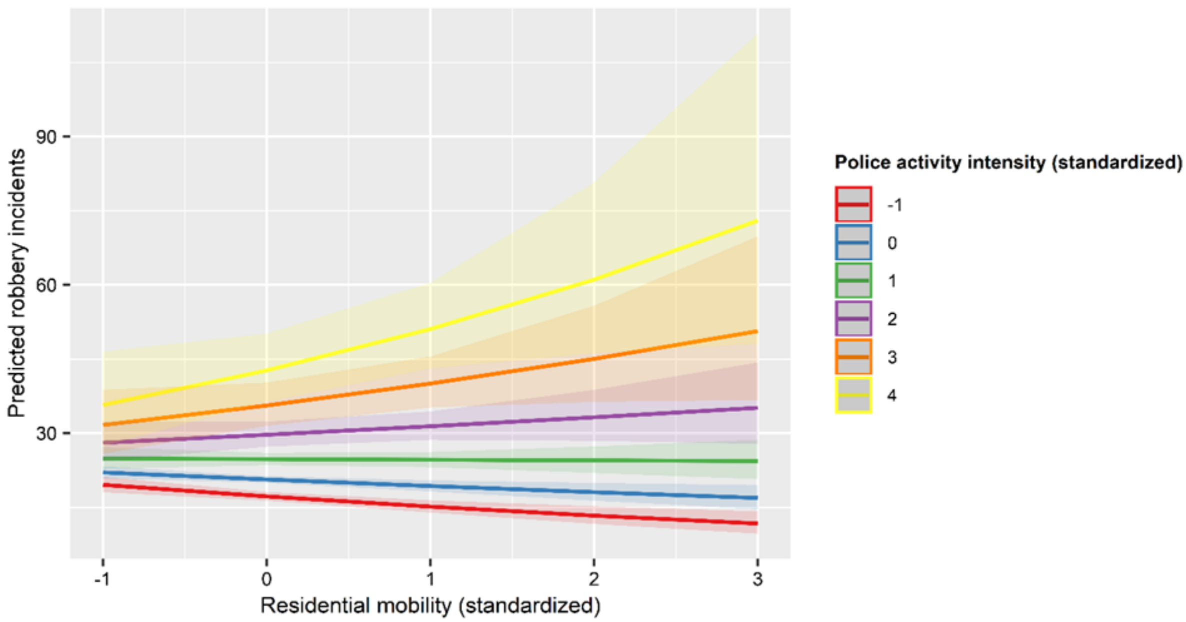


Table 6.3 presents the interaction effects between police activity intensity and collective mobility patterns on burglary rates. In Model 1, police activity intensity exhibits a significant positive main effect on burglary rates, but this effect is not observed in subsequent models. Police activity intensity significantly moderates the relationship between inward population flow and burglary rates, with a strong, positive, and highly significant interaction effect shown in Models 1, 4, and 7. However, it doesn't have a significant moderating effect on the other two mobility indicators. The interaction between outward population flow and police activity

Table 6.3

Moderation analysis for collective mobility and burglary rates in Baltimore during 2019

Variables[abc]	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Inward population flow	-0.21*** (0.02)	-0.14*** (0.04)	-0.15*** (0.04)	-0.23*** (0.01)	-0.22*** (0.02)	-0.15*** (0.04)	-0.23*** (0.02)
Outward population flow	-0.08 (0.05)	-0.16* (0.07)	-0.13* (0.06)	-0.10 (0.07)	-0.08 (0.05)	-0.14* (0.07)	-0.10 (0.07)
Residential mobility	0.04 (0.03)	0.07* (0.03)	0.06+ (0.03)	0.05+ (0.03)	0.04 (0.03)	0.07+ (0.04)	0.05 (0.03)
Police activity intensity	0.08* (0.04)	0.03 (0.04)	0.02 (0.04)	0.06 (0.04)	0.06 (0.05)	0.01 (0.05)	0.05 (0.05)
IPF*PAI	0.10*** (0.02)			0.12*** (0.01)	0.10*** (0.02)		0.12*** (0.02)
OPF*PAI		-0.03 (0.05)		-0.08^{+} (0.04)		-0.02 (0.05)	-0.07 (0.05)
RM*PAI			0.05 (0.04)		0.05 (0.03)	0.05 (0.04)	0.03 (0.03)
Structural characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Land use information	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged outcome	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Selected eigenvectors	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	198	198	198	198	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.

[a] Baseline intercept, selected eigenvectors, and covariates are not shown in the table.

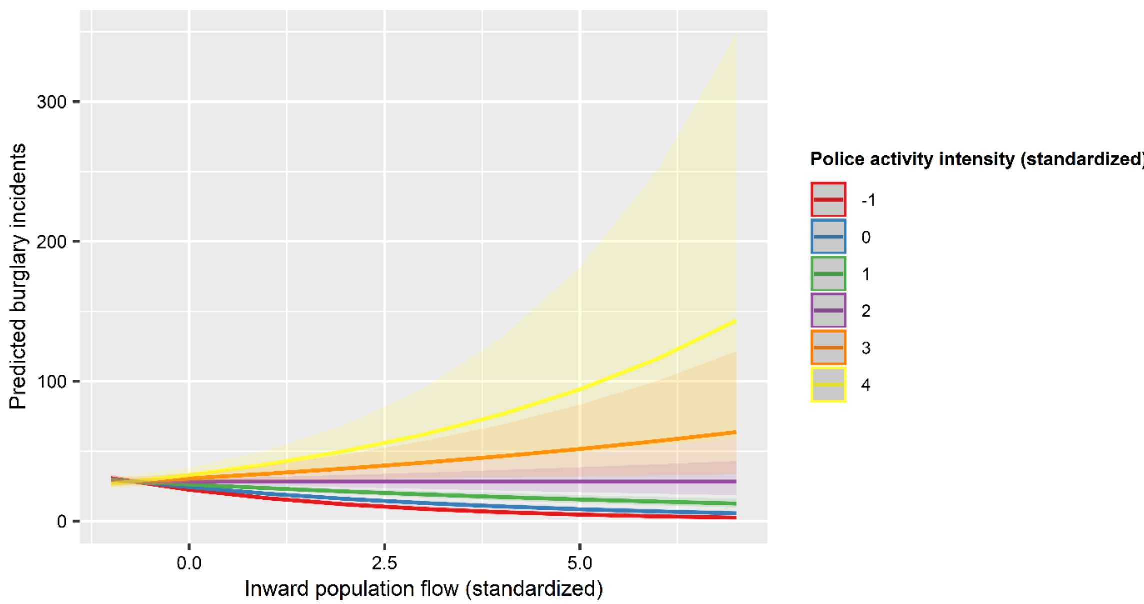
[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

[c] RM=Residential mobility, IPF=Inward population flow, OPF =Outward population flow, PAI =Police activity intensity

intensity is marginally significant in Model 5 but not in other models, while the interaction between residential mobility and police activity intensity is consistently insignificant.

Figure 6.4

The interaction plot of inward population flow and police activity towards burglary in Baltimore



I visualize the relationship between inward population flow and the predicted number of burglaries at different levels of police activity intensity in **Figure 6.4**. The steeper slopes for higher levels of police activity intensity (yellow and orange lines) indicate that the moderating effect of police presence strengthens as patrol intensity increases. In neighborhoods with low to moderate police patrol activity, where less than 30 percent of the land is classified as BPD crime hotspots (represented by the red, blue, and green lines), the association between inward population flow and burglary incidents is weak and negative. This suggests that in areas with low police presence, high inward mobility is associated with low burglary rates. Neighborhoods with high police activity intensity, particularly those where more than 60 percent of the area is designated as BPD crime hotspots (represented by the orange and yellow lines), exhibit a strong and positive relationship between inward population flow and burglary incidents: in those neighborhoods, high inward population flow corresponds to high burglary rates.

<u>Summary</u>

In summary, hypothesis 2a suggests that *neighborhoods with high levels of police patrol activity will experience higher crime rates compared to those with low levels of patrol activity*. The findings presented in this chapter partially support this hypothesis. Across all models, there is a significant positive association between police activity intensity and robbery rates, as well as in some models for burglary. However, while a positive association is observed between police activity intensity and homicide rates, it remains statistically insignificant across all models.

In hypothesis 2b, I argue that *the positive association between residential mobility and crime rates will be stronger in neighborhoods with high levels of police patrol activities compared to those with low levels*. This hypothesis receives partial support. There is no evidence that police patrol intensity significantly amplifies the relationship between residential mobility and homicide rates. Similarly, the positive interaction effects between residential mobility and police activity intensity on burglary rates are not statistically significant. However, there is some indication that police activity intensity strengthens the relationship between residential mobility and robbery rates.

Also, hypothesis 2c predicts that *the negative association between (inward and outward) population flows and crime rates will be weaker in neighborhoods with high levels of police patrol activities compared to those with low levels*. This hypothesis is partially supported. There is no evidence that police patrol intensity significantly moderates the relationship between any type of dynamic population flow and homicide rates. Some evidence suggests police activity intensity significantly moderates outward population flow and robbery rates, but the moderation effect for inward population flow and robbery rates is weak and marginally significant. A strong moderation effect is observed for inward population flow and burglary rates, where police presence alters the impact of inward mobility on burglary outcomes. Compared to that outcome, police activity intensity strengthens the negative relationship between outward population flow and burglary rates, though this effect is only marginally significant. Moreover, the initially negative association between inward and outward population flows and crime rates weakens when police activity intensity remains relatively low. As police activity increases to moderate or high levels, the nature of this relationship shifts, with the direction reversing to positive and the strength of the mobility-crime association growing progressively stronger.

Thus, while police patrol intensity does amplify some mobility-crime relationships, the type of mobility that is significantly moderated by police patrol activity differs for each crime type. In the next chapter, I explore temporal variations within mobility-crime relationships.

Chapter 7: Temporal Variations within the Mobility-Crime Connections

In this chapter, I investigate the temporal variations in collective mobility patterns, crime, and their interconnections in Baltimore during 2019. My goal here is to explore whether the relationship between collective mobility patterns and crime rates varies by time period, particularly focusing on seasonal effects and differences between weekdays and weekends. In the first section, I present descriptive trends for both monthly and intra-weekly collective mobility patterns, as well as trends for each type of crime incident. The second section examines the longitudinal relationships between inward and outward population flows and weekly crime rates, including potential seasonal variations within these relationships. In the third section, I conduct further analysis to assess whether the mobility-crime connection differs between weekdays and weekends.

Temporal variations of mobility and crime

In 2019, crime patterns in Baltimore neighborhoods exhibited distinct monthly trends. **Figure 7.1** illustrates the fluctuations in homicide, robbery, and burglary incidents throughout the year. Robbery and burglary incidents rise during the summer months and decline in winter, while homicide rates fluctuate, with higher numbers observed in late spring and early summer. Robbery (blue line) experiences its highest number of incidents in August, exceeding 550 cases, and its lowest in February, with nearly 300 cases. Burglary (green line) follows a similar seasonal trend, with incidents peaking in September at over 500 cases and reaching its lowest point in December, at around 370 cases. Homicide (red line), displayed on a separate axis due to its lower totals, varies throughout the year. It peaks in July, with nearly 40 cases, and reaches its lowest point in February, with fewer than 20 cases.

Figure 7.1

Monthly trends of crime incidents in Baltimore during 2019

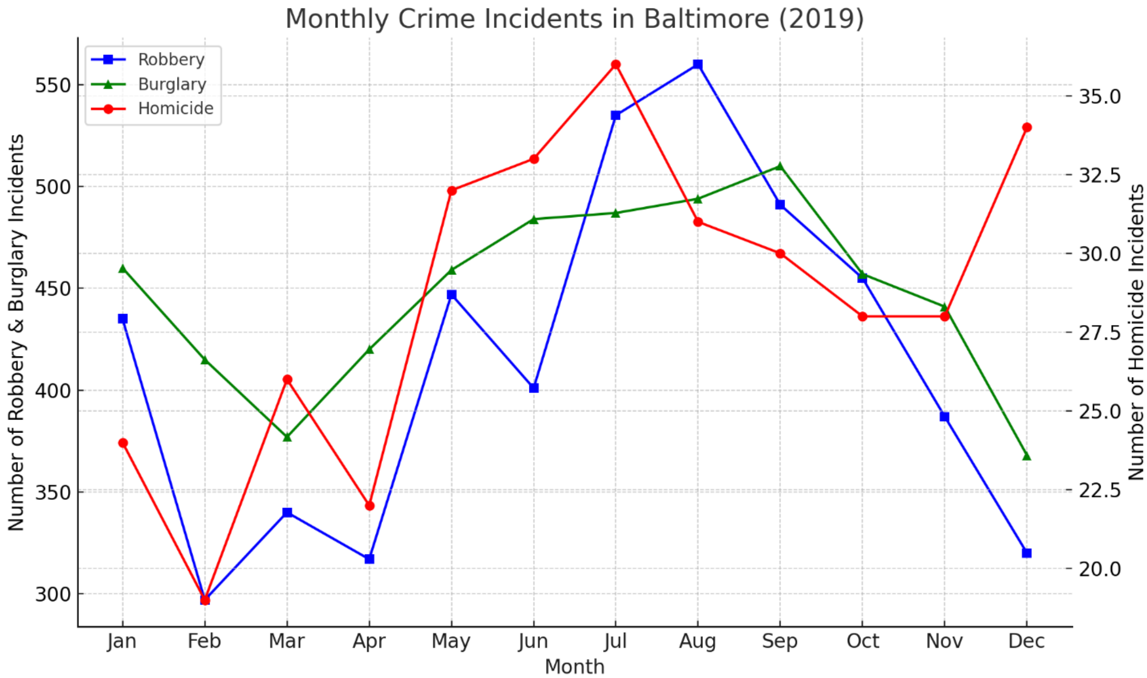


Figure 7.2 shows the distribution of homicide, robbery, and burglary incidents across each day of the week in Baltimore during 2019. Homicide (red line, right axis) peaks on Thursday, with more than 60 cases, and reaches its lowest point on Sunday, with fewer than 40 cases. This pattern suggests that homicides are more frequent mid-week and decline toward the weekend. Robbery (blue line, left axis) occurs most frequently on Tuesday, with over 770 cases, and is least frequent on Thursday, with around 670 cases. The trend indicates that robberies are more common early in the week, slightly decreasing as the week progresses. Burglary (green line, left axis) peaks on Wednesday, with approximately 840 cases, and drops to its lowest level on Sunday, with fewer than 600 cases. This suggests that burglaries are more prevalent mid-week but decline significantly by the weekend.

Figure 7.2

Intraweek trends of crime incidents in Baltimore during 2019

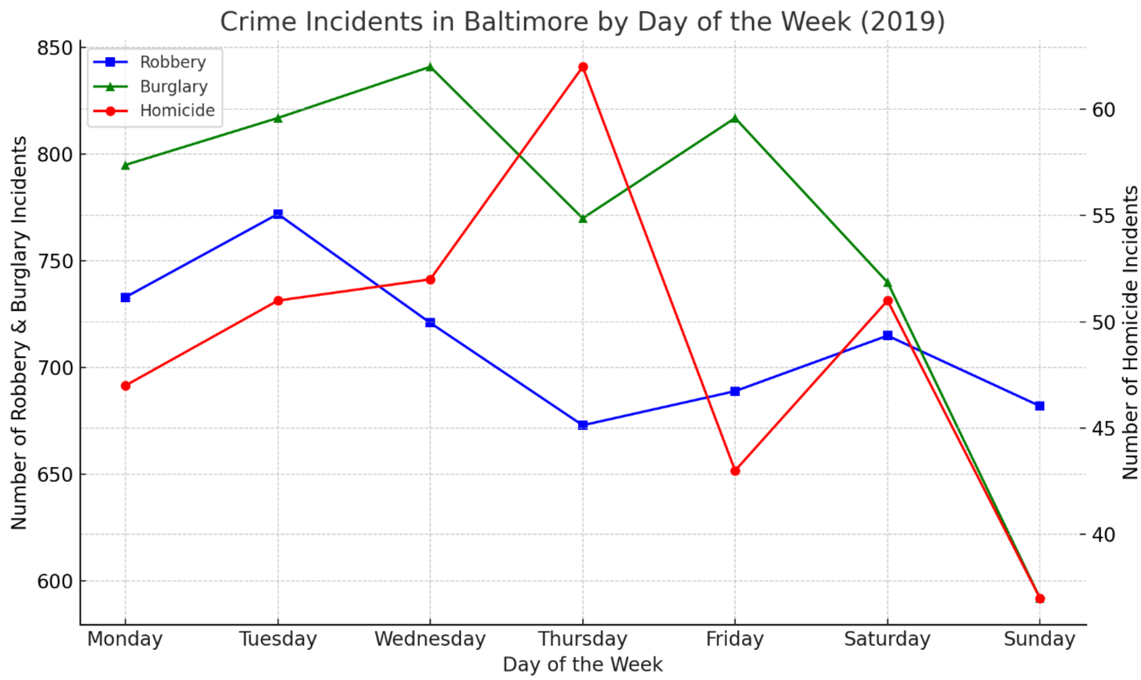


Figure 7.3

Monthly trends of population flow in Baltimore City during 2019

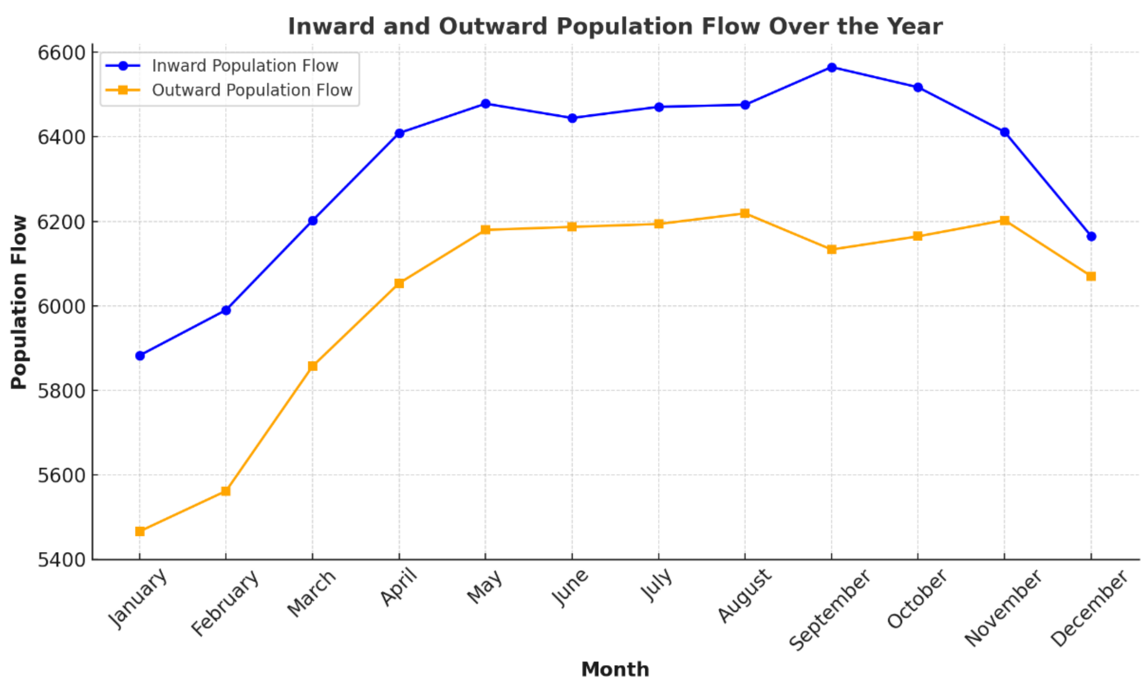


Figure 7.3 presents the monthly trends of inward and outward population flow in Baltimore during 2019. Both flows increase from January, reaching their highest levels in late summer (August–September) before gradually declining toward December. The inward population flow peaks in September at approximately 6,600, while its lowest point is recorded in January at around 5,900. Similarly, the outward flow reaches its highest level in August at approximately 6,200 and its lowest in January at around 5,400.

Figure 7.4

Intraweek trends of population flow in Baltimore City during 2019

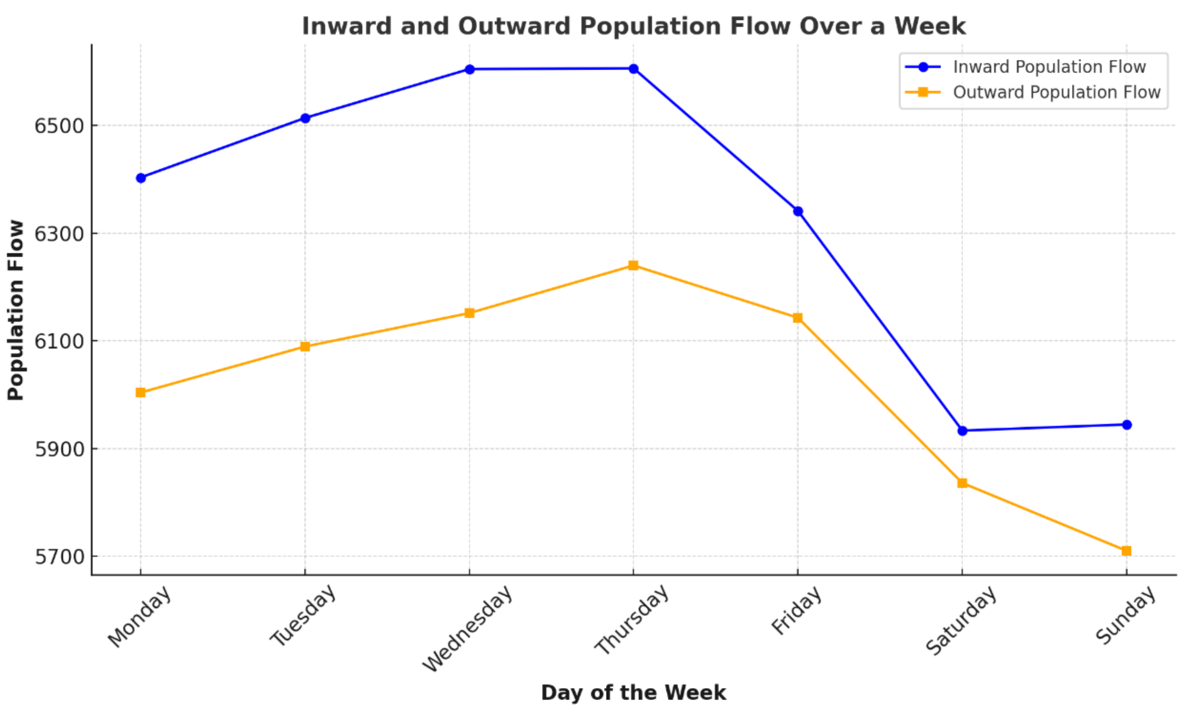


Figure 7.4 presents the intraweek trends of Baltimore's inward and outward population flow during 2019. Both flows steadily rise from Monday to Thursday, peaking on Thursday, before sharply declining toward the weekend. The highest inward and outward flows occur on Thursday, reaching approximately 6,600 and 6,250, respectively. The lowest inward flow is

recorded on Saturday at 6,000, while the lowest outward flow occurs on Sunday at approximately 5,700.

Table 7.1

Seasonal variations for weekly collective mobility and homicide rates in Baltimore

Variables[abc]	**(1)**	**(2)**	**(3)**	**(4)**
Inward population flow	-0.05	-0.06	-0.05	-0.05
	(0.07)	(0.12)	(0.07)	(0.12)
Outward population flow	0.04	0.04	0.02	0.02
	(0.08)	(0.08)	(0.13)	(0.13)
Summer	0.20	0.20	0.16	0.16
	(0.15)	(0.15)	(0.15)	(0.15)
Fall/Autumn	0.07	0.08	0.07	0.08
	(0.16)	(0.16)	(0.16)	(0.16)
Winter	-0.03	-0.03	-0.03	-0.04
	(0.16)	(0.16)	(0.16)	(0.16)
Temporal lag	-0.44	-0.44	-0.46^{+}	-0.46^{+}
	(0.27)	(0.27)	(0.27)	(0.27)
IPF*Summer		0.04		0.003
		(0.12)		(0.13)
IPF*Fall/Autumn		-0.05		-0.02
		(0.14)		(0.14)
IPF*Winter		0.03		0.05
		(0.14)		(0.14)
OPF*Summer			0.21	0.20
			(0.15)	(0.16)
OPF*Fall/Autumn			-0.15	-0.15
			(0.17)	(0.17)
OPF*Winter			-0.05	-0.07
			(0.18)	(0.18)
Number of observations	10296	10296	10296	10296

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[a] Clustered-robust standard errors in parenthesis.

[b] Baseline intercept, selected eigenvectors, and other covariates are not shown.

[c] Fixed effect is excluded due to unreliable standard errors and model convergence issues.

Seasonal variations of mobility-crime connections

Table 7.1 presents the results of a panel analysis examining the relationship between dynamic population flows and weekly homicide rates. However, neighborhood-level fixed effects are excluded due to extremely large standard errors and convergence issues when included. Nevertheless, I incorporate structural characteristics and land use patterns into the models to partially account for time-invariant factors that can bias the estimates. I find no evidence that the relationship between inward or outward population flow and homicide rate varies across seasons. In addition to showing no significant interaction effects, both inward and outward population flows exhibit statistically insignificant main effects on homicide rates.

Table 7.2 presents the effects of inward and outward population flows on weekly robbery rates, accounting for seasonal variations. The findings provide some evidence that the relationship between dynamic population flow and robbery rates differs across seasons. In Model 2, all three interaction terms involving inward population flow are statistically significant and negative. However, in Model 4, the interaction between inward population flow and the winter season becomes only marginally significant. For outward population flow, all three interaction terms are statistically insignificant in Model 3. In Model 4, only the interaction between outward population flow and the winter season is statistically significant and positive, while the interaction between outward population flow and the fall/autumn season is marginally significant. Additionally, outward population flow has a statistically significant and negative main effect on robbery rates.

Since the statistical significance of the interaction terms does not directly reveal how the slope of inward or outward population flow varies across seasons, I conduct a post-estimation analysis and utilize a margins plot to illustrate these changes.

Table 7.2

Seasonal variations for weekly collective mobility and robbery rates in Baltimore

Variables[ab]	**(1)**	**(2)**	**(3)**	**(4)**
Inward population flow	-0.10	-0.10	-0.10	-0.11
	(0.11)	(0.12)	(0.11)	(0.11)
Outward population flow	-0.21*	-0.23*	-0.20**	-0.22**
	(0.10)	(0.11)	(0.07)	(0.07)
Summer	0.31***	0.32***	0.32***	0.33***
	(0.03)	(0.03)	(0.03)	(0.03)
Fall/Autumn	0.20***	0.22***	0.19***	0.21***
	(0.04)	(0.03)	(0.04)	(0.04)
Winter	-0.09*	-0.08+	-0.10*	-0.07
	(0.04)	(0.04)	(0.04)	(0.05)
Temporal lag	0.02	0.01	0.02	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
IPF*Summer		-0.01*		-0.01*
		(0.01)		(0.01)
IPF*Fall/Autumn		-0.02***		-0.03**
		(0.01)		(0.01)
IPF*Winter		-0.03*		-0.04+
		(0.02)		(0.02)
OPF*Summer			-0.06	-0.05
			(0.06)	(0.06)
OPF*Fall/Autumn			0.08	0.09+
			(0.05)	(0.05)
OPF*Winter			0.09+	0.11*
			(0.05)	(0.05)
Number of observations	10296	10296	10296	10296

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
[a] Clustered-robust standard errors in parenthesis.
[b] Baseline intercept, selected eigenvectors, and fixed effects are not shown.

Figure 7.5 presents the predicted robbery rate across different levels of standardized inward population flow and seasons, highlighting how the relationship between inward population flow and robbery rate fluctuates across seasons. I find that the negative effect of inward population flow on robbery is significantly weaker in spring compared to the other seasons. An increase of approximately 5,100 visitors to a neighborhood corresponds to a 0.10-unit decrease in the log of the expected robbery rate during spring, translating to a 9.5% reduction. In contrast, the reduction is 10.5% in summer, 11.4% in autumn, and 12.2% in winter, indicating a stronger impact in these seasons. However, pairwise comparisons reveal that the slope estimates for summer, autumn, and winter do not differ significantly from one another.

Figure 7.5

Seasonal variations of weekly inward population flow and robbery incidents in Baltimore

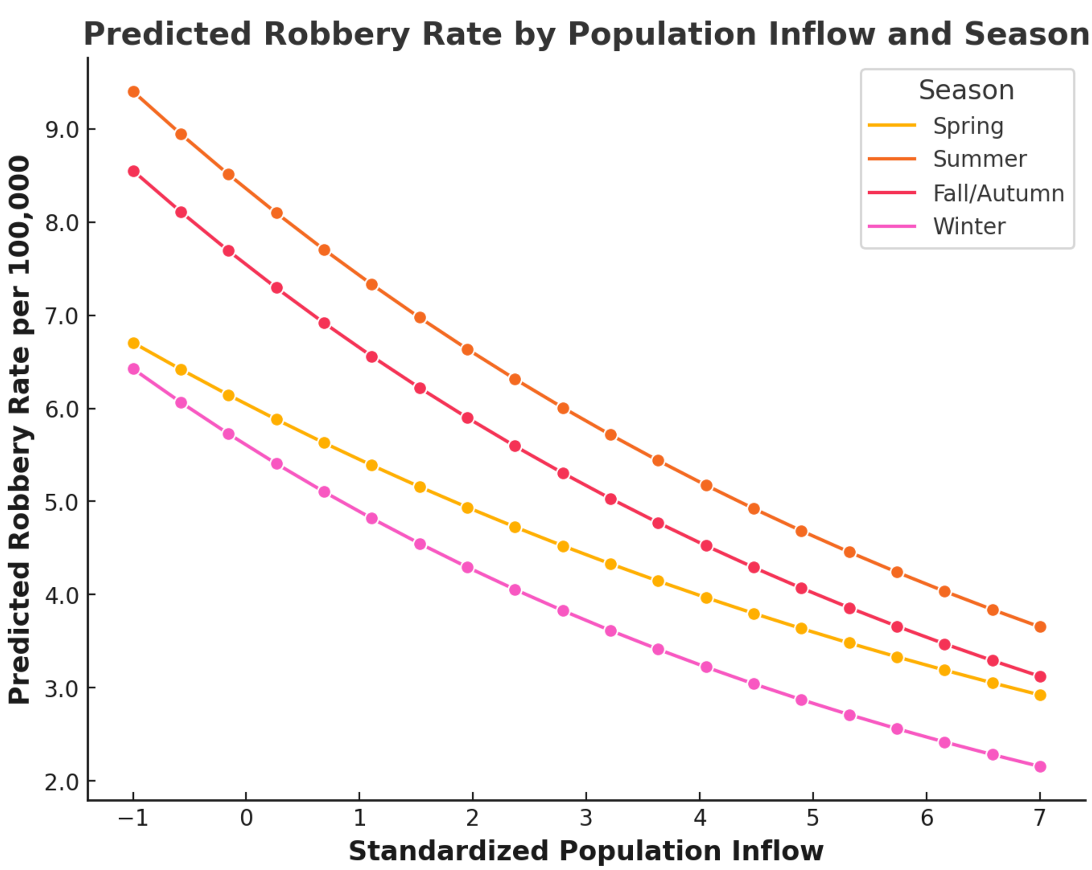


Figure 7.6 illustrates the trends in predicted robbery rates across varying levels of standardized outward population flow and different seasons. The negative relationship between outward population flow and robbery rates is notably weaker in fall/autumn and winter compared to spring and summer. In winter, the departure of approximately 2,900 individuals from a neighborhood corresponds to a 0.11-unit decline in the log of robbery rates, equating to a 10.5% reduction. For fall/autumn, this reduction is around 12.2%. In contrast, the impact is more pronounced in spring and summer, with reductions of 19.8% and 23.7%, respectively. However, the difference in slope estimates between spring and summer, as well as between fall/autumn and winter, are not statistically significant.

Figure 7.6

Seasonal variations of weekly outward population flow and robbery incidents in Baltimore

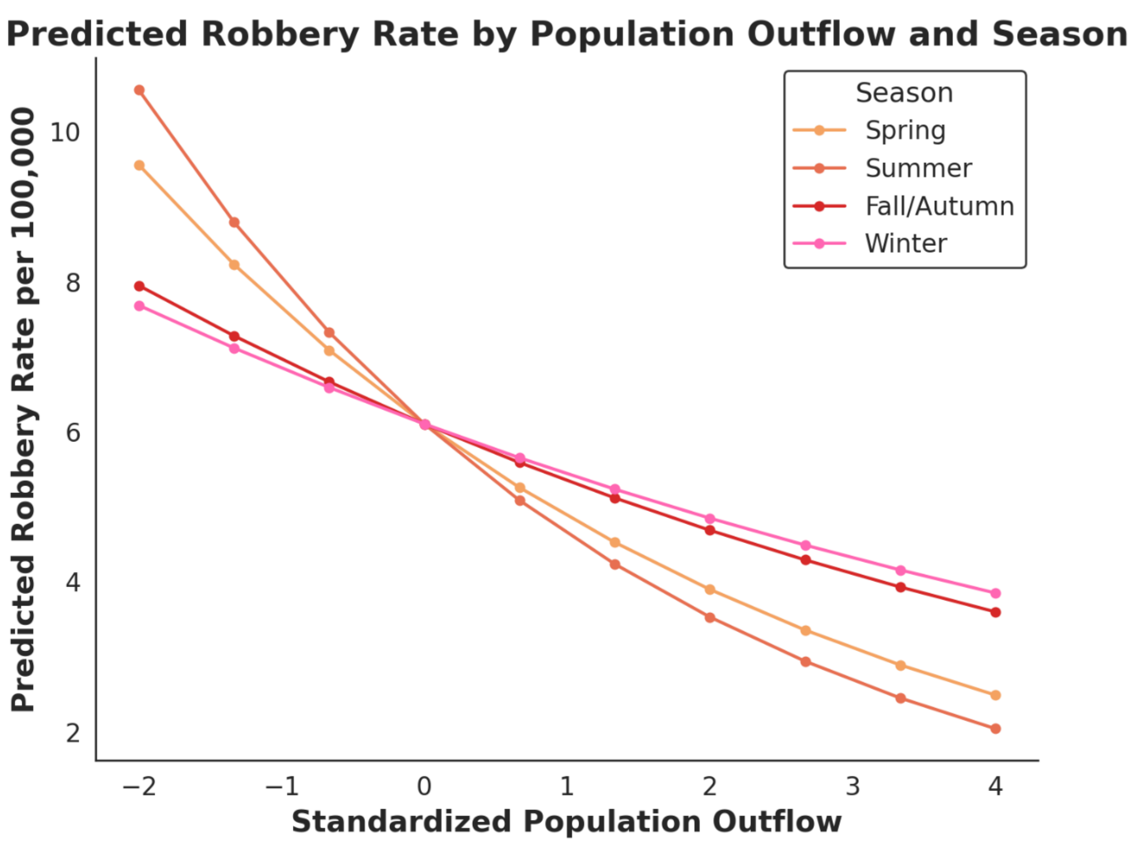


Table 7.3

Seasonal variations for weekly collective mobility and burglary rates in Baltimore

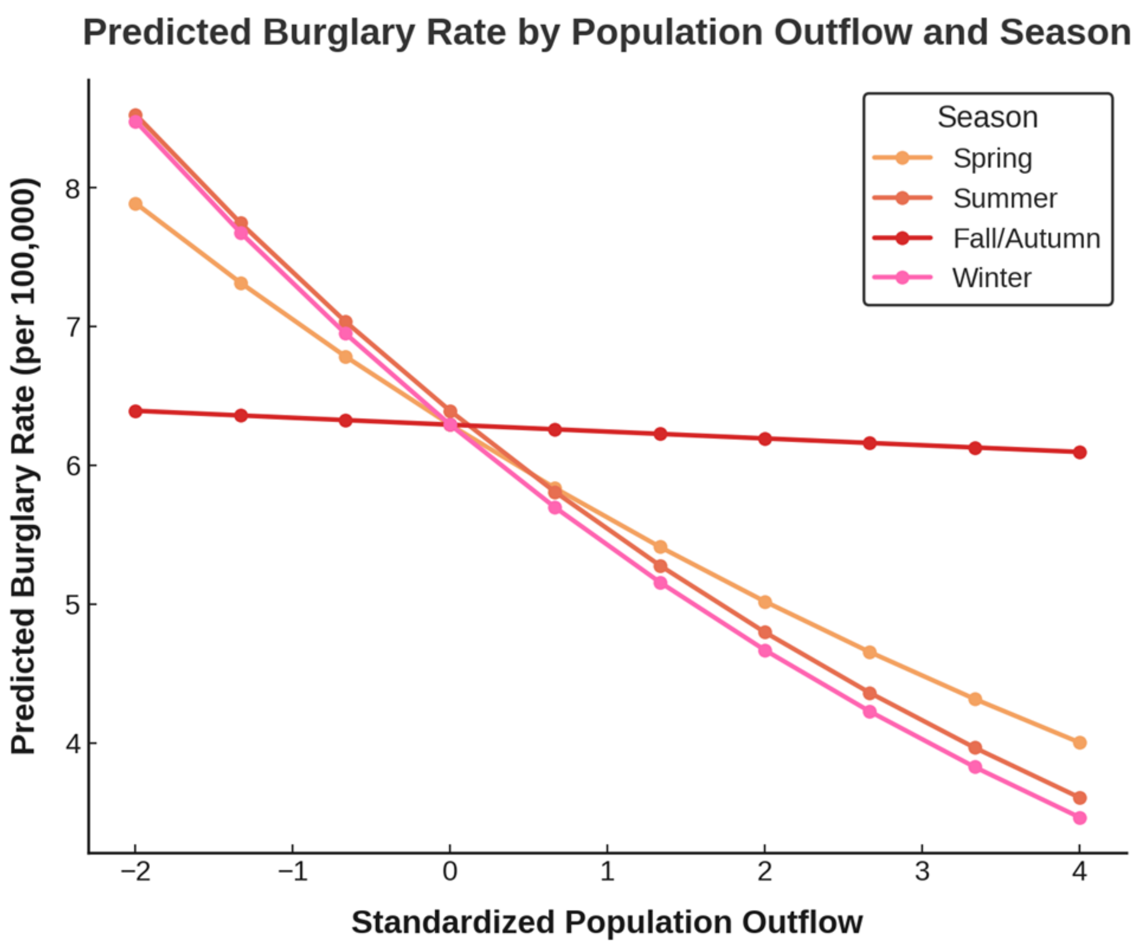
Variables[ab]	**(1)**	**(2)**	**(3)**	**(4)**
Inward population flow	-0.19*	-0.20+	-0.19*	-0.20+
	(0.09)	(0.11)	(0.09)	(0.11)
Outward population flow	-0.05	-0.05	-0.12	-0.11
	(0.17)	(0.17)	(0.16)	(0.17)
Summer	0.12*	0.13*	0.14**	0.14*
	(0.05)	(0.05)	(0.05)	(0.05)
Fall/Autumn	0.10	0.09	0.07	0.07
	(0.07)	(0.07)	(0.07)	(0.07)
Winter	-0.06	-0.06	-0.06	-0.06
	(0.08)	(0.08)	(0.08)	(0.08)
Temporal lag	0.06***	0.06***	0.06***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)
IPF*Summer		-0.003		0.001
		(0.01)		(0.02)
IPF*Fall/Autumn		0.03		0.02
		(0.02)		(0.02)
IPF*Winter		0.003		0.01
		(0.03)		(0.03)
OPF*Summer			-0.03*	-0.03+
			(0.02)	(0.02)
OPF*Fall/Autumn			0.11*	0.11*
			(0.05)	(0.05)
OPF*Winter			-0.03	-0.04
			(0.05)	(0.05)
Number of observations	10296	10296	10296	10296

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
[a] Clustered-robust standard errors in parenthesis.
[b] Baseline intercept, selected eigenvectors, and fixed effects are not shown.

The week-level analysis of burglary rates reveals patterns distinct from those observed for robbery rates. **Table 7.3** outlines the effects of inward and outward population flows on weekly burglary rates while accounting for seasonal variations. Among these factors, outward population flow is the only variable with statistically significant interaction terms. In contrast, inward population flow demonstrates a significant negative main effect but does not exhibit any significant seasonal variations in its slope.

Figure 7.7

Seasonal variations of weekly outward population flow and burglary incidents in Baltimore



I further illustrate in **Figure 7.7** how the relationship between outward population flow and predicted burglary rates varies across seasons. In fall/autumn, this relationship is significantly weaker than in other seasons, with outward population flow having little to no effect on burglary rates. In contrast, an increase of 2,900 individuals leaving a neighborhood in spring is associated with a 0.12-unit decrease in the log of the expected burglary rate, equivalent to an approximately 11.4% reduction. For summer and winter, this reduction is around 14%. Additionally, there are no significant differences in the effect of outward population flow on burglary rates across these three seasons.

Table 7.4

Weekday-weekend variations for daily collective mobility and homicide rates in Baltimore

Variables[ab]	**(1)**	**(2)**	**(3)**	**(4)**
Inward population flow	-0.09*	-0.09*	-0.09*	-0.10*
	(0.04)	(0.04)	(0.04)	(0.04)
Outward population flow	0.07	0.07	0.08	0.09
	(0.08)	(0.08)	(0.08)	(0.08)
Summer	0.22	0.22	0.22	0.22
	(0.18)	(0.18)	(0.18)	(0.18)
Fall/Autumn	0.08	0.08	0.08	0.08
	(0.20)	(0.20)	(0.20)	(0.20)
Winter	0.01	0.01	0.01	0.01
	(0.21)	(0.21)	(0.21)	(0.21)
Weekend	-0.09	-0.09	-0.09	-0.09
	(0.15)	(0.15)	(0.14)	(0.15)
Temporal lag	-0.37	-0.37	-0.37	-0.37
	(0.61)	(0.61)	(0.61)	(0.61)
Inward population flow*Weekend		0.01		0.04
		(0.14)		(0.12)
Outward population flow*Weekend			-0.08	-0.10
			(0.14)	(0.14)
Number of observations	72072	72072	72072	72072

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
[a] Clustered-robust standard errors in parenthesis.
[b] Baseline intercept, selected eigenvectors, and other covariates are not shown.

Intraweek variations of mobility-crime connections

I next examine whether the relationship between dynamic population flows and crime rates differ between weekdays and weekends. **Table 7.4** uses the daily number of dynamic flows as well as homicide rates in Baltimore and investigates whether the relationship between inward and outward population flow and predicted homicide rates differs between weekdays and weekends. Across all models, an increase in inward population flow is significantly associated with lower homicide rates, while outward population flow and weekend mobility interactions show no significant effects. However, this finding should be interpreted with caution, as I exclude neighborhood-level fixed effects, and include only structural characteristics and land use patterns in those models to partially account for potential confounding factors.

Table 7.5

Weekday-weekend variations for daily collective mobility and robbery rates in Baltimore

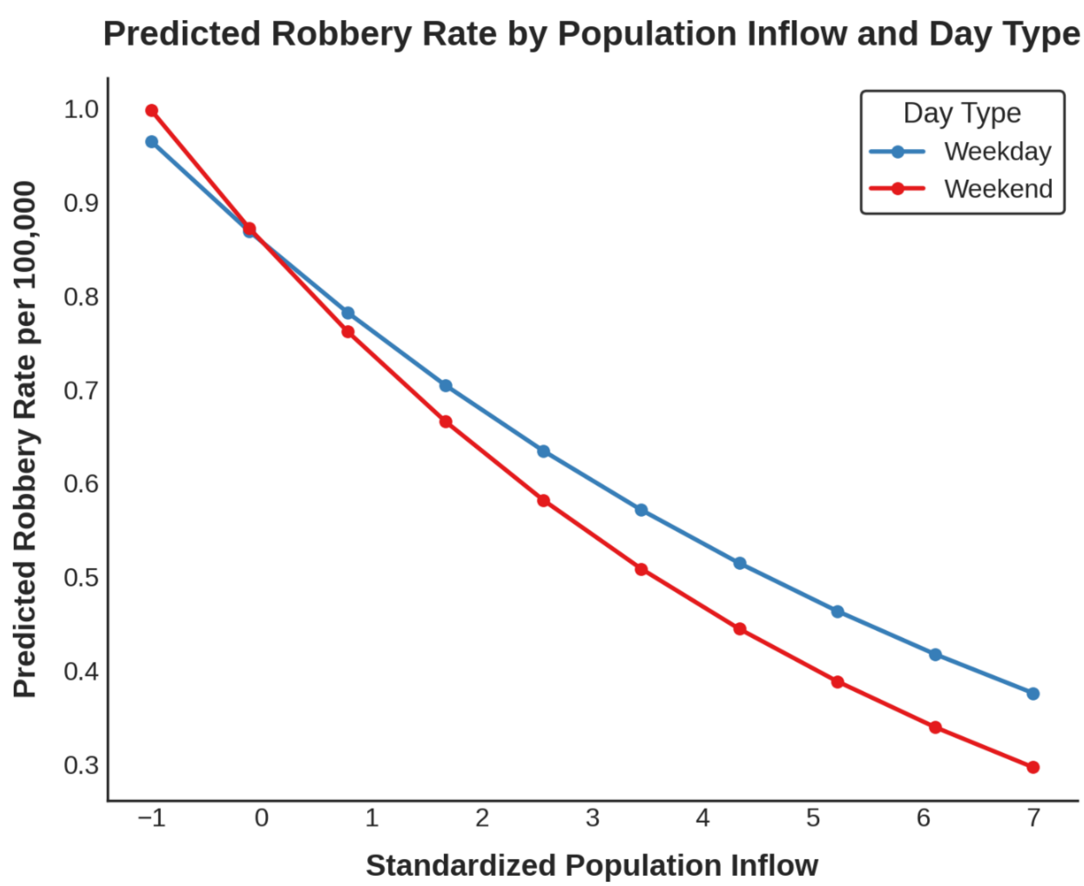
Variables[ab]	**(1)**	**(2)**	**(3)**	**(4)**
Inward population flow	-0.15*	-0.16*	-0.15*	-0.16*
	(0.07)	(0.06)	(0.07)	(0.06)
Outward population flow	-0.11*	-0.11*	-0.11*	-0.11*
	(0.05)	(0.05)	(0.05)	(0.05)
Summer	0.31***	0.31***	0.31***	0.31***
	(0.03)	(0.03)	(0.03)	(0.03)
Fall/Autumn	0.21***	0.21***	0.21***	0.21***
	(0.04)	(0.04)	(0.04)	(0.04)
Winter	-0.01	-0.01	-0.01	-0.01
	(0.04)	(0.05)	(0.04)	(0.05)
Weekend	0.004	0.02	0.003	0.01
	(0.04)	(0.04)	(0.04)	(0.04)
Temporal lag	0.08**	0.08**	0.08**	0.08**
	(0.02)	(0.02)	(0.02)	(0.02)
Inward population flow*Weekend		-0.04+		-0.04*
		(0.02)		(0.02)
Outward population flow*Weekend			0.02	0.04
			(0.04)	(0.04)
Number of observations	72072	72072	72072	72072

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
[a] Clustered-robust standard errors in parenthesis.
[b] Baseline intercept, selected eigenvectors, and fixed effects are not shown.

Next, I summarize the key findings from **Table 7.5**, which examines the relationship between daily inward and outward population flows and predicted robbery rates, as well as potential weekday-weekend differences. The results indicate that outward population flow remains a significant predictor of robbery rates, while the negative association between inward population flow and robbery rates also becomes statistically significant at the daily level. Additionally, I find limited evidence that the interaction between inward population flow and robbery rates is statistically significant and negative in Models 2 and 4, emphasizing the need for post-hoc analysis to clarify this slope difference. However, there is no indication of a significant slope difference for outward population flow between weekdays and weekends.

Figure 7.8

Intraweek variations of daily inward population flow and robbery rates in Baltimore



I illustrate the potential slope difference in the relationship between inward population flow and robbery rates across weekdays and weekends in **Figure 7.8**. I find that the negative relationship between inward population flow and robbery rates is stronger on weekends than on weekdays. For every 5,400 additional people arriving in a neighborhood, the log of expected robbery rates decreases by 0.16 units, which equals a 14.8% decrease in robbery rates on weekdays. This reduction is even larger on weekends, reaching 18.2% for the same increase in inward population flow.

Table 7.6

Weekday-weekend variations for daily collective mobility and burglary rates in Baltimore

Variables[ab]	**(1)**	**(2)**	**(3)**	**(4)**
Inward population flow	-0.22***	-0.22***	-0.22***	-0.22***
	(0.03)	(0.02)	(0.03)	(0.03)
Outward population flow	0.04	0.04	0.04	0.04
	(0.06)	(0.06)	(0.06)	(0.06)
Summer	0.16***	0.16***	0.16***	0.16***
	(0.05)	(0.05)	(0.05)	(0.05)
Fall/Autumn	0.12+	0.12+	0.12+	0.12+
	(0.08)	(0.08)	(0.08)	(0.08)
Winter	0.04	0.03	0.03	0.03
	(0.07)	(0.07)	(0.07)	(0.07)
Weekend	-0.17***	-0.16**	-0.16***	-0.16**
	(0.05)	(0.05)	(0.05)	(0.05)
Temporal lag	0.17***	0.17***	0.17***	0.17***
	(0.04)	(0.04)	(0.04)	(0.04)
Inward population flow*Weekend		-0.05*		-0.05*
		(0.02)		(0.02)
Outward population flow*Weekend			-0.04	-0.03
			(0.04)	(0.04)
Number of observations	72072	72072	72072	72072

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[a] Clustered-robust standard errors in parenthesis.

[b] Baseline intercept, selected eigenvectors, and fixed effects are not shown.

Table 7.6 summarizes the relationship between inward and outward population flow and burglary rates, examining whether these patterns differ between weekdays and weekends. I find a similar weekday-weekend difference in the effect of dynamic population flows on burglary rates. The negative relationship between inward population flow and burglary rates remains statistically significant across all models at the daily level. More importantly, the interaction between inward population flow and the weekend indicator is also significant, indicating the need for further analysis to confirm whether this effect is stronger on weekends than weekdays. However, there is no evidence that outward population flow significantly affects burglary rates or that its impact varies between weekdays and weekends.

Figure 7.9

Intraweek variations of daily inward population flow and burglary rates in Baltimore

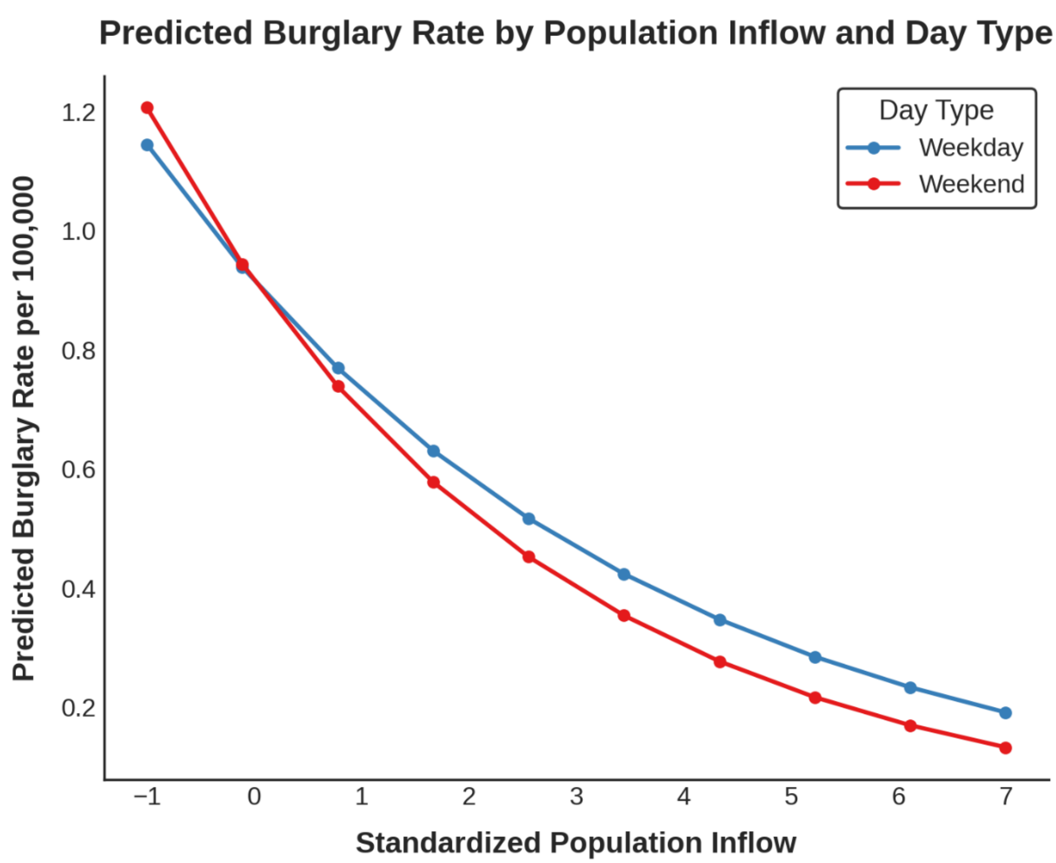


Figure 7.9 illustrates the variation in the slope of inward population flow on predicted burglary rates, comparing weekdays and weekends. I find that on weekdays, an increase of 5,400 visitors in a neighborhood links to a 0.22-unit decrease in the log of expected burglary rates, translating to a 19.8% reduction in burglary rates. On weekends, the same increase in inward flow results in a 0.27-unit decrease, equivalent to a 23.7% reduction, indicating a significantly stronger reduction effect compared to weekdays.

<u>*Summary*</u>

Hypothesis 3a suggests that *the negative relationship between high inward and outward population flows and low crime rates will be stronger during summer (June through August) than in other seasons.* However, the results do not support this hypothesis: I find some evidence of seasonal variation in the relationship between dynamic population flows and crime rates, but the patterns do not align with the expected outcomes outlined in the hypothesis. There is no evidence of a significant relationship between inward or outward population flow and homicide rates varying across seasons. For robbery, post-estimation results indicate no significant differences in the effect of inward population flow across summer, autumn, and winter, nor the impact of outward population flow between spring and summer. Similarly, for burglary, the relationship between inward population flow and crime does not vary significantly across seasons, and outward population flow shows no significant seasonal differences in its association with burglary rates.

Hypothesis 3b posits that *the negative relationship between high inward and outward population flows and low crime rates will be stronger on weekends (Saturday & Sunday) than on weekdays.* This hypothesis is partially supported for robbery and burglary, but not for homicide. For robbery, the negative association between inward population flow and robbery rates is stronger on weekends than on weekdays. A similar pattern emerges for burglary, where the decrease in burglary rates linked to increased inward population flows is greater on weekends than on weekdays. However, the relationship between inward or outward population flow and homicide rates does not significantly differ between weekdays and weekends.

Chapter 8: Discussion and Conclusion

In this chapter, I elaborate on the major findings by giving a summary of the results and how they relate to the research questions and relevant hypotheses. I outline the key patterns observed, while paying specific attention to how collective mobility patterns interact with crime rates and how these relationships change across space and time. Furthermore, I discuss the study's limitations by acknowledging factors that could have impacted the results, including but not limited to data constraints, omitted variables, and methodological limitations. Finally, I discuss the broad implications of the findings from theoretical, empirical, and policy perspectives. This also includes recommendations for future research directions, and conclusions on how understanding the relationship between mobility and crime may provide insights into urban safety, crime prevention strategies, and community-police interactions.

Recap of research questions and hypotheses

In this study, I set out to explore the relationship between collective mobility patterns and urban crime dynamics, with Baltimore serving as the focal point. The primary objectives are to determine whether shifts in collective mobility patterns— reflected in changes in inward and outward population flows and residential mobility—are associated with variations in homicide, robbery, and burglary rates in Baltimore in 2019. To guide this investigation, I structure this study around three research questions, each accompanied by specific hypotheses:

RQ1: Are collective human mobility patterns significantly associated with crime rates in Baltimore?

- ***H1a:*** Higher residential mobility will be associated with higher rates of crime.

- ***H1b:*** Higher (inward and outward) mobility flows will be associated with lower rates of crime.
- ***H1c:*** Inward population flow will be associated with larger decreases in robbery rates than burglary rates.
- ***H1d:*** Outward population flow will be associated with larger decreases in burglary rates than robbery rates.

RQ2: Does the relationship between collective mobility and crime vary by the distribution of police patrol activities?

- ***H2a:*** Neighborhoods with higher levels of police patrol activities will have higher crime rates compared to neighborhoods with lower levels of police patrol activities.
- ***H2b:*** the positive association between residential mobility and crime rates will be stronger in neighborhoods with high levels of police patrol activities compared to those with low levels.
- ***H2c:*** the negative association between (inward and outward) population flows and crime rates will be weaker in neighborhoods with high levels of police patrol activities compared to those with low levels.

RQ3: Does the relationship between collective mobility and crime vary over time?

- ***H3a:*** The negative relationship between high inward and outward population flows and low crime rates will be stronger during summer (June through August) than in other seasons.

- ***H3b:*** The negative relationship between high inward and outward population flows and low crime rates will be stronger on weekends (Saturday & Sunday) than weekdays.

I formulate these research questions and corresponding hypotheses to address several key gaps in the literature. First, while many studies have focused on individual mobility patterns, collective movements have received less attention (Felson & Boivin, 2015; Kadar et al., 2015; Sugie & Lens, 2017). Second, before the advent of advanced mobile device location data, available sources and measures were often insufficient to capture the dynamic features of mobility patterns (Browning et al., 2021; Cagney et al., 2020). Third, although residential mobility and inward population flows have been widely examined, other indicators—such as outward population flow—remain underexplored (Law et al., 2014; Mahfoud et al., 2021; Pridemore & Grubesic, 2012). Fourth, the variability of local security measures (e.g., police patrol adjustments) may influence the relationship between collective mobility and crime victimization (Malleson & Andresen, 2015, 2016; R. B. Taylor et al., 2015). Fifth, beyond spatial variations, temporal fluctuations may also affect the relationship between collective mobility and crime. The composition and purpose of daily travelers can change over the seasons, potentially altering how mobility impacts crime (Mahfoud et al., 2021; Ruktanonchai et al., 2021; Wesolowski et al., 2017; Zufiria et al., 2018). Finally, differences between weekdays and weekends warrant exploration, as variations in visit purposes, types of activities, and duration of stays can further modify the mobility–crime connection (Andresen & Malleson, 2015; Bernasco et al., 2017; W. D. Lee et al., 2021; G. Song et al., 2023; Tucker et al., 2021). Together, those gaps highlight the importance of a comprehensive investigation into the mobility–crime relationship—one that incorporates both spatial and temporal dimensions—to gain deeper insight into the dynamics of crime victimization risk.

Summary of key findings

The primary analyses provide substantial evidence regarding the complex interplay between collective human mobility and crime rates in Baltimore. First, with respect to **RQ1**, the findings provide partial support for the hypotheses underlying this question. In line with **Hypothesis 1a**, high residential mobility is associated with high burglary rates, although it does not significantly relate to homicide or robbery rates in most cases. Consistent with **Hypothesis 1b**, both inward and outward population flows generally exhibit a negative association with crime: inward population flows significantly reduce robbery rates, and both flows are linked to lower burglary rates. Notably, neither flow shows a significant relationship with homicide, suggesting that the effects of collective mobility are crime-specific.

Also, **Hypothesis 1c** is partially supported, as evidence suggests that the increase in inward population flow is linked to a greater reduction in robbery rates compared to burglary rates, but only after accounting for structural characteristics, land use patterns, and prior robbery levels. **Hypothesis 1d** is also partially confirmed, as outward population flow demonstrates a more consistent negative relationship with burglary. However, its initially strong impact on robbery rates significantly weakens after accounting for prior crime levels. Basically, those results reveal a complex interplay where the influence of collective mobility on crime depends on both the type of mobility measure and the specific crime outcome.

Secondly, addressing **RQ2**, the spatial analyses reveal mixed results for this research question. I find a significant positive association between police activity intensity and crime rates, primarily for robbery and burglary, providing partial support for **Hypothesis 2a**. In general, the results indicate no significant moderation effect on homicide rates. However, for robbery and burglary, there is evidence that police patrol intensity moderates the impact of certain mobility measures. Specifically, residential mobility exhibits stronger effects on robbery rates as the intensity of police activity increases. However, there is no significant interaction effect between residential mobility and police activity intensity on burglary rates, which suggests that **Hypothesis 2b** is not fully supported.

In addition, I observe a strong positive moderation effect in the relationship between inward population flow and burglary rates, and outward population flow exhibits a moderated effect on robbery rates. However, police activity intensity exhibits a marginally significant positive moderation effect on the relationship between inward population flow and robbery rates. It further strengthens the negative relationship between outward population flow and burglary rates, though this effect is also marginally significant. These findings suggest that while police presence can influence some mobility–crime relationships, its effects are not universal, making **Hypothesis 2c** limitedly supported.

Thirdly, with respect to **RQ3**, longitudinal analyses reveal that the mobility–crime relationship varies over time. Although statistically significant seasonal variations exist in the relationship between dynamic population flows and crime rates, these variations do not conform to the expected pattern outlined in **Hypothesis 3a**. In contrast, **Hypothesis 3b**—predicting more substantial mobility–crime associations on weekends than weekdays—is partially supported. Specifically, inward population flow more strongly reduces robbery and burglary rates on weekends than weekdays, while outward population flow shows no significant weekday–weekend differences.

Overall, these findings demonstrate the importance of considering crime-specific effects, spatial context, and temporal variation when examining the dynamics of collective mobility and crime in urban settings.

Discussion

The findings provide important insights into the relationship between collective mobility patterns and crime, revealing both expected and unexpected patterns. First, the analysis shows that high residential mobility significantly predicts increased burglary rates, consistent with findings from prior work. This finding aligns with previous studies that have established a strong positive relationship between residential turnover and burglary (Bernasco & Luykx, 2003; Peeters et al., 2018). It corresponds with the social disorganization perspective, which posits that frequent residential turnover undermines social cohesion and community stability, diminishes informal social control, and increases chances for property crimes such as burglary (Shaw & McKay, 1942).

Meanwhile, unlike the findings of Stults and Hasbrouck (2015), residential mobility continues to be a significant predictor even after accounting for the impact of dynamic population flows on burglary rates. Stults and Hasbrouck (2015) have found that the effects of residential mobility on crime rates decrease substantially and become statistically insignificant after incorporating the number of incoming commuters as an additional predictor. However, while this is the case for robbery rates, the same pattern does not hold for burglary rates in the current study. This is because successful burglaries usually require offenders to be familiar with residential vulnerabilities, which develop over time rather than through temporary population fluctuations (Bernasco & Nieuwbeerta, 2005). Besides, long-term residential instability creates opportunities for burglary through two main mechanisms. First, it generates physical vulnerabilities during transition periods: properties are left unattended or temporarily unoccupied, doors are left open during moves, valuables are exposed, and maintenance may decline between tenants (Piza & Carter, 2018; Rey et al., 2012). Second, it erodes social controls since neighbors who move often are less familiar with one another and are, therefore, less able to spot strangers or questionable behavior (Levy et al., 2020; Sampson et al., 1997). This diminished familiarity hinders the growth of mutual trust necessary for group responses to possible issues and reduces informal surveillance. The main difference is that, even while neighborhoods may see significant daily population movements, protective social institutions are undermined by a persistent pattern of residence change (Kubrin & Weitzer, 2003). The frequent turnover of long-term residents hinders the development of strong social ties and community supervision that normally discourage burglaries, especially in places with high daily foot traffic or tourist activity (Sampson & Groves, 1989; Sampson & Raudenbush, 1999).

Second, contrary to several previous studies, inward population flow consistently presents a negative impact on crime rates in Baltimore. Unlike most previous research that either incorporates inward population flow solely into the ambient population for crime rate calculations (Andresen & Jenion, 2010; Malleson & Andresen, 2016), or treats it exclusively as a primary predictor of changes in crime counts or probabilities (G. Song et al., 2019, 2023), this study takes a dual approach. I integrate the measure of inward population flows alongside the residential population to account for variations in the population at risk while also acknowledging it as an important predictor of changes in crime rates. Compared to studies that use crime rate as an outcome and list inward flow as a major predictor, the consistent negative impact of inward flows on robbery and burglary rates in this study aligns with findings from Andresen (2007, 2011). However, it contrasts with other studies suggesting that daily incoming commuters and tourists contribute to higher rates of violence (Grinols et al., 2011; Stults & Hasbrouck, 2015; Tucker et al., 2021).

The differences in findings may be attributed to contextual variations in study areas. Given that Baltimore is a mid-sized city with higher crime rates than most cities examined in previous research, differences in urban characteristics and crime trends may explain why inward population flow shows a negative impact in this study but a positive impact in others (Stults & Hasbrouck, 2015). Also, Tucker et al. (2021) and Grinols et al. (2011) have examined a broader range of crime types than the current study, suggesting that the relationship between inward flows and crime may vary by offense type. For instance, their findings suggest that violent crimes, including assault and rape, increase with greater inward flows, whereas property crimes like burglary and auto theft exhibit a negative association. Further, those findings challenge the traditional assumption that higher population inflows inherently increase crime risk by introducing more potential offenders. Still, my findings align with Cohen and Felson's (1979) routine activities approach and Jacobs's (1961) concept of "eyes on the street," with the former highlighting the role of capable guardianship in crime prevention and the latter suggesting that areas with high pedestrian activity and community visitation experience low crime rates due to increased informal monitoring. Based on both perspectives, an increased number of incoming visitors can enhance informal surveillance and community presence, reducing opportunities for crime through increased public visibility and informal social control, thereby disrupting criminal activities and deterring potential offenders.

Third, this study advances the understanding of collective mobility patterns and crime by demonstrating the substantial effects of outward population flow, a dimension largely overlooked in previous research. While previous studies have primarily examined inward population flow and its potential role in either increasing or reducing crime rates (Andresen, 2011; Tucker et al., 2021), this finding reveals a complex dynamic by highlighting the critical role of outward mobility. Specifically, I find that outward population flow serves as a protective factor against crime, suggesting that the daily departure of individuals may disrupt established patterns of criminal opportunity and victimization. This finding aligns with the situational opportunity perspective and challenges traditional assumptions about dynamic population movement and crime, which have often focused exclusively on the effects of incoming visitors. Those results indicate that understanding neighborhood crime patterns requires consideration of both inward and outward population movements, as these movements can have distinct, and sometimes type-specific, effects on crime rates.

The protective effect of outward population flow can be understood through its relationship with the underlying population dynamics and social interactions in neighborhoods. Areas with high outward flow typically have substantial baseline populations that naturally generate large volumes of daily movement out of the area (Felson & Boivin, 2015). These outward movements do not simply represent residents temporarily leaving their neighborhoods—they actively foster important social interactions among those departing, those staying, and newcomers. As people move out, their mobility reshapes how activity spaces are used, enhancing informal surveillance by increasing street-level observation and creating more opportunities for informal monitoring (Andresen & Jenion, 2010). Consequently, crime rates decline due to enhanced surveillance mechanisms and the presence of numerous guardians (Linning & Eck, 2021; McMillen et al., 2019). Again, this finding underscores the importance of disaggregating dynamic population movements when studying neighborhood crime patterns, as focusing solely on inward population flow provides an incomplete picture of how short-term fluctuations within collective mobility patterns shape urban crime rates.

Building upon this, the distinct, crime-specific effects of inward and outward population flow on robbery and burglary rates require careful consideration. These findings suggest that the two crime types respond differently to dynamic population movements, likely due to variations in their spatial distribution and necessary opportunity structures. Unlike in many other cities, the number of robbery incidents in Baltimore is nearly equal to that of burglary (Andresen & Jenion, 2010; Tucker et al., 2021). However, while burglary incidents are widely distributed across neighborhoods, robberies are highly concentrated in a few specific areas, which may contribute to the varying relationships between population flows and crime rates. This distinction also stems from the fundamental differences in the conditions required for each crime: robbery necessitates direct confrontation with victims, whereas burglary typically occurs when occupants are absent (Bernasco et al., 2017; Mahfoud et al., 2021). An increase in inward population flow populates public spaces, increasing the likelihood of witnesses and reducing the effectiveness of force or threats, thereby discouraging robbery (Connealy, 2021). In contrast, high outward population flow leads to greater vigilance among the remaining residents, prompting them to adopt heightened security measures to protect themselves and their homes (Browning et al., 2010). This increased awareness and precautionary behavior raise the chances of detecting or disrupting burglary attempts, ultimately lowering the success rate for burglars (Bernasco & Nieuwbeerta, 2005).

Fourth, the presence of spatial variations in the mobility-crime relationship, influenced by intense police activity, extends findings from previous studies. The strong positive association between police activity intensity and robbery and burglary rates aligns with the "recording effect," which suggests that increased law enforcement efforts may lead to higher reported crime rates (J. MacDonald et al., 2016; Pina-Sánchez et al., 2023). Increased police presence leads to higher detection and reporting of offenses that might have previously gone unnoticed or unreported, creating the illusion of a crime increase (Ashby & Tompson, 2017; Koper, 1995). Also, offenders may respond to heightened enforcement by altering their behavior, such as shifting locations or adopting new tactics, resulting in a temporary spike before law enforcement fully regains control (Averdijk et al., 2016; Bernasco & Block, 2011). Besides, the impact of residential mobility on robbery rates becomes even stronger in neighborhoods with heightened police activity. Stable communities foster strong networks and a collective willingness to maintain safety, whereas high residential mobility disrupts this cohesion, making crime control more reliant on law enforcement (Braakmann, 2023; H. Lee & Perkins, 2023; Piza & Carter, 2018). As police activity intensifies in these neighborhoods with medium or high levels of residential mobility, the absence of resident-driven crime prevention becomes increasingly apparent, reinforcing the link between residential mobility and robbery rates.

On the other hand, these results regarding spatial variation should be interpreted with caution. Using the coverage of BPD crime hotspots as a proxy for police patrol intensity suggests that neighborhoods with heightened police activity are those with extensive crime hotspot coverage, reflecting a long-standing and complex history of crime. The observed positive connection between police activity intensity and crime rates, along with the moderating effect of police patrol intensity, may primarily reflect the close connections between local crime risks and corresponding police responses. This raises concerns about endogeneity, as crime hotspots and law enforcement responses are inherently interdependent (Wu et al., 2022). As a result, it becomes difficult to determine whether crime hotspots drive increased police presence and interventions, or whether heightened police presence directly impacts crime rates in those neighborhoods. Therefore, the current study serves as an introduction to this topic. Future research should develop rigorous measures to overcome the endogeneity limitation.

Fifth, somewhat distinct from previous studies, I find that the negative effect of inward population flow on robbery and burglary rates is more pronounced on weekends than on weekdays. This finding is consistent with some previous studies (G. Song et al., 2023; Tucker et al., 2021), but contrasts with others (Andresen & Malleson, 2015; Bernasco et al., 2017), highlighting the ongoing debate regarding the intraweek dynamics of mobility and crime. The varying composition of individuals engaged in daily population movements, including the differing distribution of residents, commuters, and visitors across weekdays and weekends, may help explain the observed patterns in mobility-crime relationships. Tucker et al. (2021) suggest that weekday population flows are primarily composed of daily commuters traveling to work, whom offenders may perceive as more attractive targets than other types of travelers. In contrast, weekends bring a different mix of individuals, often drawn to the city for leisure activities, whose presence may have less impact than weekday commuters on crime. Besides incoming visitors for education, holidays, and other purposes, the effect of travel by residents and employees (individuals who commute to the neighborhood for work) varies between weekdays and weekends, shaping crime patterns in distinct ways (G. Song et al., 2023). During weekdays, a large majority of residents (i.e., employees) commute to their workplaces: they spend most of their time indoors at work, with limited outdoor exposure mainly during their commuting time. In contrast, remaining residents may stay home or travel certain distances to participate in outdoor activities (Yuan & Raubal, 2016). These outdoor activities increase residents' exposure to potential confrontations with robbers, while homes left temporarily unoccupied by residents or employees create opportunities for burglars. To some extent, these factors mitigate the negative impact of incoming population flow on robbery and burglary. On weekends, however, neighborhoods become livelier than on weekdays as children, adolescents, and young adults return from kindergarten, school, and higher education institutions. This creates ample opportunities for family gatherings and outdoor interaction. Additionally, most employees have greater flexibility on weekends, allowing them to spend more time outdoors for leisure and entertainment, remaining in the area for extended periods (G. Song et al., 2023). As a result, stronger guardianship and reduced vulnerability among residents and employees, along with the consistent flow of visitors who serve as additional witnesses and guardians, contribute to a stronger negative effect of inward population flows on robbery and burglary rates during weekends compared to weekdays.

In addition to the findings that align with my hypotheses, there are also unexpected or statistically insignificant results that merit further discussion. I want to highlight that the relationship between dynamic population flows and robbery and burglary rates shifts as police activity intensifies. Specifically, in neighborhoods with medium to high levels of police activity, I observe a strong positive mobility-crime association, with outward population flows linked to higher robbery rates and inward population flows associated with increased burglary rates. One possible explanation is that intensely policed areas frequently coincide with high-crime, high-mobility locations, where the convergence of motivated offenders, suitable targets, and weakened guardianship creates conditions conducive to crime. While law enforcement presence can deter criminal activity, it does not eliminate opportunities for crime; rather, it may make them more detectable, altering the observed link between dynamic population flows and crime (Ashby & Tompson, 2017; Koper, 1995; Santos & Santos, 2015). At the same time, limited resources force police to concentrate their patrol efforts in specific areas, typically crime hotspots, which may leave other parts of the neighborhood more vulnerable to crime. This uneven distribution of enforcement can also contribute to potential increases in crime rates (Andresen & Malleson, 2014; Gelman et al., 2007; Telep et al., 2014).

The inconsistent spatial variations within the mobility-crime connection suggest that the moderating effect of police activity intensity is not uniform across different contexts. Instead, it varies depending on the specific type of crime and the nature of mobility involved. Robberies typically occur in public spaces, and the presence of newcomers through inward mobility may reduce robbery rates, regardless of police activity intensity (Boivin, 2018; Gerell, 2021). As the number of daily visitors increases, the neighborhood becomes more populated and socially active, inevitably altering its social and environmental dynamics. This shift directly reduces robbery opportunities, operating independently of police intervention. Also, since police activity primarily targets micro-level crime hotspots, its influence on the overall relationship between inward population flow and robbery rates may be minimal when examined at a broader level, such as neighborhood/census tract.

Compared to robberies, burglaries often target unoccupied residences. While high residential mobility can result in more vacant homes or temporary residents, the breakdown of social cohesion and weakened informal social control may play a more significant role in shaping the relationship between residential mobility and burglary rates than police patrols and other law enforcement activities alone (Braakmann, 2023; Santos & Santos, 2015; Xie & McDowall, 2008). Since police cannot continuously monitor every home, the presence of stable residents providing informal surveillance is crucial. While patrols can help deter crime, they primarily respond to incidents rather than prevent burglaries in advance (Mahfoud et al., 2021;

Piza & Carter, 2018; Santos & Santos, 2015). In neighborhoods with high residential turnover, law enforcement may also struggle to gather reliable witness reports, further reducing their effectiveness in influencing the connection between residential mobility and burglary rates (Antrobus & Pilotto, 2016).

I find limited evidence suggesting that high police activity intensity reinforces the negative relationship between outward population flow and burglary rates. This moderation effect is only marginally significant, and I interpret the results cautiously. On the one hand, burglars often rely on predictable routines to identify targets (Robinson, 1999; Rountree & Land, 1996). High outward mobility disrupts these patterns, making it harder for potential offenders to predict which homes will be unoccupied. Therefore, if outward movements are prevalent in certain neighborhoods, burglars may perceive their households as less attractive, reducing the overall burglary rates regardless of police presence. On the other hand, neighborhoods experiencing high outward population flow still see a greater decline in burglary rates compared to those with a low volume of outward movements. As outward population flow increases, the remaining residents become more vigilant (G. Song et al., 2019). When police activity intensifies, it further enhances this vigilance, effectively compensating for the reduced number of people in the area by providing additional guardianship (Rey et al., 2012; Santos & Santos, 2015). This combined effect makes burglary riskier for offenders, strengthening the negative relationship between outward population flow and burglary rates.

The seasonal trends in longitudinal mobile-crime relationships remain ambiguous and inconclusive. As one of the major cities in Maryland, Baltimore experiences relatively consistent patterns of population movement in and out throughout most of the year. This stability in urban dynamics helps maintain a steady relationship between inward and outward population flow and crime rates during most seasons. Employment- and education-related movements are generally predictable, with most people commuting to the city for work or studies year-round, aside from brief holiday breaks (Boivin, 2018; Felson & Boivin, 2015). Consequently, even if school or university-related travel decreases during the summer, this reduction is offset by increased tourist visits during the same period. In winter, while fewer people on the streets might lower the chances for robberies, the concentration of people in indoor spaces and the surge in foot traffic in commercial areas for holiday shopping provide alternative opportunities for robbery, effectively balancing out the reduced street activity (Kim & Wo, 2022). As a result, the fluctuations in different types of travelers within dynamic population movements create a compensatory effect throughout the year, where declines in one category of travelers or commuters are often counterbalanced by increases in another. This relative balance makes it challenging to identify clear and consistent seasonal patterns in the relationship between population flow and crime rates.

I also find no evidence that the relationship between outward population flow and any of the three crime outcomes differs between weekdays and weekends. The consistent impact of outward population flow from weekdays to weekends suggests that as people leave areas, changes in guardianship—such as the presence of more witnesses or potential helpers—affect crime rates similarly, whether individuals are departing for work during the weekdays or for leisure on the weekends (Boivin & Felson, 2018; G. Song et al., 2019). For example, in the case of burglaries, unoccupied homes and businesses present equally attractive targets to burglars, regardless of whether it is a weekday or weekend (Piza & Carter, 2018). Since burglary incidents are more likely when spaces are unoccupied, the specific day someone leaves may be less important than the time of day they depart (Felson & Poulsen, 2003; Towers et al., 2018).

Burglars are more likely to target homes during the daytime, particularly when residents are away due to work or school schedules (Coupe & Blake, 2006; Doleac & Sanders, 2015). However, this study cannot capture the time-of-day variations due to data limitations.

Inconsistent findings on seasonal and intraweek variations in mobile-crime connections may also be influenced by temporal shifts in law enforcement strategies and patrol priorities. These changes can alter the relationship between dynamic population flows and crime rates, potentially obscuring expected seasonal or weekday-weekend patterns**.** Law enforcement strategies may shift with the seasons (Boivin & Felson, 2018; Kim & Wo, 2022). In spring and summer, heightened outdoor activity typically leads to enhanced active patrolling and visible security measures, offsetting the potential effect of population flows on crime rates (Malleson & Andresen, 2015). Conversely, during autumn and winter, as activities shift indoors or become less frequent due to weather conditions, policing tactics may adapt accordingly. This shift can reduce informal street surveillance while increasing vigilance and prioritizing security measures in indoor activity areas, transportation hubs, and tourist attractions (Haberman et al., 2018; Hipp et al., 2004).

Police departments can further adjust their tactics based on the day of the week. On weekdays, deployment primarily targets high-activity areas—such as business districts, transit hubs, and commercial zones—where many workers and commuters are present (Braga & Weisburd, 2010; Weisburd et al., 2010). On weekends, the focus shifts to areas where social activities and gatherings elevate crime risks, including entertainment districts, nightlife hotspots, and public venues that draw large crowds (Braga & Weisburd, 2010; B. Welsh et al., 2024). Additionally, transportation hubs and major event venues receive more police patrols on weekends than on weekdays due to the higher population and the resulting rise in crime opportunities (Weisburd et al., 2012). As a result, those strategic adjustments in policing may contribute to collective mobility patterns' inconsistent or diminished effects on crime rates across different temporal contexts, making it more challenging to detect clear seasonal or weekday-weekend trends.

It is important to note that almost all major findings related to homicide rate as the outcome were not statistically significant. This may be due to the low base rate of homicides. In 2019, nearly half of Baltimore neighborhoods reported no homicides, and even the highest-risk neighborhoods recorded a maximum of ten cases. This number is much lower than the average and peak incident counts for robbery and burglary during the same period. The low base rate of homicides limits the statistical models' power to detect meaningful mobility-crime relationships or significant moderating effects of police patrol activity, as there are not enough variations in this outcome across neighborhoods. This issue becomes even more serious in the longitudinal analysis—when homicides are broken down into weekly and daily counts for rate calculations, most neighborhoods report zero incidents in most periods, resulting in little temporal variation.

Another possible explanation is that, compared to robbery and burglary, homicide incidents are less opportunistic and, therefore, less influenced by changes in collective mobility patterns. In contrast to robberies and burglaries, homicides often stem from interpersonal conflicts (Kalesan et al., 2018), gang retaliation (Pyrooz, 2012), or premeditated violence (Ploeg et al., 2024), rather than the product of spontaneous encounters between possible victims and offenders (Bernasco et al., 2017; Mahfoud et al., 2021). Additionally, my analysis shows that structural factors, such as the disadvantage index, the young male population, and housing vacancy, significantly influence homicide rates. This suggests that persistent structural disadvantages and demographic characteristics may primarily drive neighborhood homicides

(Baumer et al., 1998; Becker, 2016; Berg et al., 2012; Kubrin & Weitzer, 2003), while short-term fluctuations in dynamic population flows have little impact on their occurrence (Boggess & Hipp, 2010; G. Tita & Griffiths, 2005). Consequently, I cannot rule out the possibility that homicide is less influenced by collective mobility because it is deeply embedded in structural and social conditions rather than immediate environmental opportunities.

Limitations

Several limitations of this study should be acknowledged. First, the demographic coverage of mobile device location data may be limited, as some individuals are not captured—either because they do not use or carry cell phones while traveling, or because their device signals are not picked up by data providers (Browning et al., 2021). *SafeGraph* mobility data underrepresent older individuals, those from lower socioeconomic backgrounds, and non-White populations (Cheng et al., 2025; Y. Zhang et al., 2023). Additionally, this bias varies depending on factors such as location, time, urbanization, and geographic scale. Significant differences also exist among mobile device location data from various providers with respect to the proportion of individuals captured, the nature of the information provided, and the precision of location tracking (Noi et al., 2022). *SafeGraph* coverage rates fluctuate from year to year, ranging from 4.5% to 14.5%, with the most stable period occurring in 2019 (Z. Li et al., 2024). More studies assessing the reliability of mobile device location data for such applications are still emerging (Hu et al., 2021; Huang et al., 2021; Kwiatek et al., 2024; Noi et al., 2022).

Second, considering the *SafeGraph* data's population coverage and Baltimore's unique characteristics, the generalizability of this study may be limited. Its findings cannot be generalized to major metropolitan areas with extensive subway networks (such as New York City) or rural regions marked by low population density and low baseline crime rates (Kwiatek et al., 2024). For cities like NYC, the tracking accuracy of GPS pings is significantly reduced within underground railway systems, making it difficult to record travelers' detailed routes accurately. In rural areas, the low base rates of various crime types make it challenging to analyze the mobility-crime relationship without aggregating crime data across different neighborhoods or periods. This aggregation makes spatiotemporal analysis difficult, hindering the ability to uncover nuances within the relationship or leading to unreliable estimates.

Third, for cell phone users whose signals are captured by *SafeGraph* devices, demographic information is typically unavailable due to anonymity and privacy requirements (Cheng et al., 2025; Kang et al., 2020; McCormick et al., 2017). This prevents me from further unpacking the mobility-crime relationship, and examining potential variations due to different demographic factors. Prior research shows that individuals from ethnic and racial minority groups are significantly less inclined to travel to affluent or predominantly white middle-class neighborhoods (Levy et al., 2020; Phillips et al., 2021; Sampson & Levy, 2020; Q. Wang et al., 2018), and the travel distance of residents is highly dependent on other factors, such as race/ethnicity, gender, and age (Ackerman & Rossmo, 2015; Luo et al., 2016). Privacy concerns prevent companies from disclosing identifiable information to address these issues.

Fourth, the current dataset records visitor flows between census tracts as the origin and destination points. Still, it does not provide information about the specific routes or the number of flows passing through each census tract along the way. The detailed route of mobility flow remains unknown, and the count of flows passing through each census tract is omitted from the dataset. In addition to inward and outward population flows examined in this study, population flows passing through one or more census tracts to reach their destinations can also contribute to variations in victimization risks among the census tracts they traverse. To gain a more comprehensive understanding of individuals in neighborhoods—including newcomers, passersby, departing residents, and those who remain—future studies should aim to incorporate measures that dynamically represent mobility patterns for both visitors and residents (Boivin & Felson, 2018; Gerell, 2021).

Fifth, in this dissertation, I concentrate on the prevalence of crime rates for 2019 and do not incorporate any longitudinal assessment of the relationship between collective mobility patterns and crime rates over the years. This poses a challenge as the researchers have the collection of residential mobility or population loss information typically on a yearly basis (Hipp et al., 2009; Hipp & Chamberlain, 2023), while the estimation of inward population flows can be tracked down to the daily level or even segmented by daytime/night or by hours (Haleem et al., 2021; Liu et al., 2022). Since both factors fall within the realm of collective mobility patterns, future research should consider using a multi-level or mixed-effect design to provide a comprehensive understanding of the mobility-crime connection.

Additionally, because the analysis is conducted at the census tract level, it does not account for variations in mobility flows that occur between different locations within the same tract, such as movements between individual census blocks. This may result in underestimating the effects of dynamic population flows and local variation in victimization risk brought by collective movement within census tracts. As certain institutions start providing detailed cellphone-based mobility data at the census block group level—balancing research accuracy with user privacy—future research should delve deeper into examining collective mobility patterns at this meso-level scale. Such an exploration could shed light on how these patterns contribute to local crime risks and the distribution of hotspots at micro-geographical levels.

Finally, there are potential drawbacks associated with using the coverage of BPD crime hotspots as a proxy variable to measure the intensity of police patrol activities. A major issue, briefly highlighted in the previous section, is the endogeneity problem; crime levels and police patrol activities influence each other simultaneously (Wu et al., 2022). This interdependence complicates determining a clear causal order between changes in crime patterns and variations in police strategies and tactics. Since crime counts and rates are the primary outcome of interest in this dissertation, using hotspot coverage derived from historical neighborhood crime data to predict contemporary crime levels also raises concerns about redundancy. The predictor (hotspot coverage) and the outcome (crime counts/rates) measure a similar underlying phenomenon—crime risk. Several researchers have made efforts to use GPS data to record officer movements and subsequently reflect variations in police presence across different areas (Hutt et al., 2021; Khalfa et al., 2024). Such alternative measures, gradually introduced in some large U.S. cities (Dau et al., 2023), offer promising solutions to the issues of relying solely on crime hotspot coverage. Therefore, future studies should utilize these alternative measures if they become available in Baltimore City.

In short, I refrain from making any causal claims about the connection between collective mobility patterns and crime, especially considering that the statistical significance of the connections between police patrol activity intensity (BPD hotspot coverage as the proxy) and robbery rates persists even after accounting for mobility factors and their interaction terms. Deciphering and precisely measuring crime opportunities continues to pose a formidable challenge for the field of criminology.

Implications

In this section, I explore in greater depth the ways in which this project can advance the field of criminology. Specifically, I examine its contributions from three key perspectives: theoretical, by refining existing frameworks; methodological, by introducing innovative measures and analytic approaches to research; and policy-related, by highlighting its potential implications for crime prevention and law enforcement.

I. Theoretical implications

The current study offers an integrated theoretical perspective addressing limitations in prior criminological theories. Traditional neighborhood approaches, such as social disorganization theory, typically perceived shifts in human mobility as gradual and slow-moving (Bursik & Grasmick, 1993; Sampson et al., 1997; Shaw & McKay, 1942). Those theories have predominantly emphasized long-term migration or residential instability as critical variables, neglecting the impact of short-term shifts in population movement on crime, as routine activities theory suggests (Cohen & Felson, 1979). In the current study, I take both the traditional neighborhood approach and the situational opportunity perspective seriously, recognizing their complementary contributions to understanding crime patterns. I integrate dynamic (inward and outward) population flow and residential mobility from each perspective, situating them within the framework of collective mobility patterns, and simultaneously examining their roles in the prevalence of crime incidents. By integrating both perspectives, this study acknowledges the enduring influence of long-term migration and residential turnover, while also highlighting how short-term fluctuations in mobility patterns create situational opportunities for crime. This dual approach allows for a more comprehensive understanding of how crime rates are shaped by both structural neighborhood characteristics and real-time changes in population flows. I endeavor to take a comprehensive approach by considering short-term population movements while accounting for residential mobility as a long-term indicator of collective mobility patterns. I argue that the situational opportunity perspective is a more suitable theoretical framework that aligns more closely with this study's micro-level focus on daily, directional, and dynamic population movements across different areas, as opposed to the traditional neighborhood approach, which focuses on long-term structural changes within neighborhoods (P. J. Brantingham et al., 2020; Cohen & Felson, 1979; Shaw & McKay, 1942; Wilson & Kelling, 1982).

The current study advances environmental criminology by providing a deeper understanding of routine activities theory, particularly in relation to dynamic human mobility. Decades after the emergence of routine activities theory (RAT), capturing the dynamic and dispersed risk of victimization is still a challenge. as crime occurs within a complex web of human interactions across different locations and periods. A key difficulty lies in unpacking how motivated offenders, potential targets, and capable guardians converge or fail to converge in specific places and moments (Cohen & Felson, 1979). While extensions of RAT, such as crime pattern theory, have provided additional insight into the spatial and temporal aspects of criminal behavior, they have not fully accounted for the role of collective mobility patterns in shaping crime risk (P. L. Brantingham & Brantingham, 1993). In this study, I argue that understanding collective human mobility patterns is essential for explaining variations in criminal opportunities across both spatial and temporal dimensions. Daily movements—whether in the forms of commuting, leisure travel, or residential relocation—continuously shift the distribution of crime opportunities, influencing where and when offenses are likely to occur. By integrating dynamic inward and outward population flows into the RAT framework, this study helps bridge the gap between traditional environmental criminology and emerging research on human mobility, offering a more nuanced understanding of how crime risks evolve in response to population movements. Advances in data collection and measurement technologies have further reduced the challenge of tracking individual or population movement trajectories across different locations over extended periods. The introduction of the latest generation of mobile device location data, a resource researchers have gradually gained access to, has significantly advanced our ability to track and measure collective population movement (Kang et al., 2020; Noi et al., 2022). By utilizing mobile device location data and recognizing the volumes, trends, and shifts in collective mobility patterns as a potential mechanism for facilitating crime, this study contributes to the situational opportunity perspective. It provides valuable insights for both empirical research and policy development (J. Lynch, 2018).

II. Methodological implications

This study goes beyond traditional statistical analyses by incorporating innovative big data sources that track dynamic population movements in daily life across various contexts. Capturing collective mobility patterns requires data from large cohorts of individuals, making the data collection process particularly challenging. Additionally, effectively measuring and representing the dynamic nature of collective mobility depends on access to appropriate data sources (Browning et al., 2021; Noi et al., 2022). Only a few studies have explored collective human mobility patterns using innovative data sources capable of capturing mobility flows within the broad ecological framework (Hipp & Kim, 2019; McCormick et al., 2017; Saxon, 2021; G. Song et al., 2023). By combining official records with big data, this study offers a more dynamic and representative assessment of human mobility patterns compared to most prior research.

This study further shows that understanding how the relationship between collective mobility patterns and crime victimization varies across spatial and temporal dimensions can contribute to the growing body of literature examining the mobility-crime relationship. It also yields valuable insights into the dynamics of crime victimization risks (Ashby & Tompson, 2017; Cagney et al., 2020). The current study has found evidence that spatiotemporal variations exist within the mobility-crime relationship, as reflected by the moderating role of police patrol activity, as well as seasonal and intra-week variations. As I have accounted for both spatial and temporal autocorrelations in the panel analysis, with fixed effects included to adjust for unobserved, time-invariant neighborhood characteristics, the current study reveals subtleties within the relationship between mobility and crime, mirroring the victimization risks experienced by Baltimore residents in their daily lives (He et al., 2020; Hipp et al., 2019; Perlman & Roy, 2021).

III. Policy implications

The insights from this study offer valuable guidance for developing more targeted approaches to public safety, with implications for both law enforcement and policymaking. These approaches aim not only to enhance safety outcomes but also to contribute to broader goals of social equity. The Baltimore Police Department's (BPD) current hotspot strategy—primarily grounded in historical crime data—has been subject to criticism, particularly in the wake of the Freddie Gray incident (White et al., 2018). This research proposes the integration of mobile device location data as a complementary tool for hotspot identification, emphasizing mobility patterns within neighborhoods as an alternative lens. Such an approach may reveal high-risk areas that traditional crime data alone would fail to capture (Hibdon et al., 2021; Hibdon & Groff, 2014). By aligning police interventions and resource distribution with collective movement patterns, BPD could improve crime prevention efforts, enhance public safety, and foster stronger, more positive relationships with the communities they serve.

Future Research

The successful application of collective mobility patterns in diverse domains has fueled a growing interest in reassessing collective human mobility patterns within the field of criminology. Still, more research is needed. Here, I identify several topics or areas that can advance our understanding of the mobility-crime relationship. First, scholars can explore whether different mobility modes present (in)variant effects on crime opportunities in Baltimore. The aggregated measure of mobility flows employed in the current study includes walking, riding bicycles or motorcycles, driving personal vehicles, and taking public transit, such as light rails and buses. Some studies argue that the crime opportunities generated from the concentration of walking in public spaces can be substantially different from those of vehicular traffic (Browning et al., 2021; Gilderbloom et al., 2015). However, the data source used in the current study does not allow me to distinguish between transportation modes. Therefore, gaining access to specific modes of mobility or using machine learning to predict relevant information is a worthy topic.

Second, besides the temporal variation discussed in the current study, the impact of the COVID-19 pandemic on collective human mobility patterns and its subsequent effect on crime rates can be an important topic for further exploration. There have been a number of studies assessing the effect of the COVID-19 pandemic on various aspects of daily lives, including changes in crime rates (Abrams, 2021; Boman & Gallupe, 2020, 2020; Bullinger et al., 2021; Campedelli et al., 2020, 2021; Felson et al., 2020; J. M. Miller & Blumstein, 2020; Mohler et al., 2020; Stickle & Felson, 2020). However, most of these prior studies examining shifts in crime patterns resulting from COVID-19 have not analyzed crime trends and urban mobility changes at a comparable scale, and they often ignore or fail to accurately measure collective mobility patterns (Halford et al., 2020; Newton et al., 2014; Paramasivan et al., 2022). Future research should consider using mobile device location data to accurately reflect the daily variations of population movement, and combine that with existing crime data to study the potential impact of the pandemic on crime, and whether such impact is transmitted or reflected through the changes in collective mobility patterns.

Third, the potential influence of gentrification on the mobility-crime relationship is another topic worthy of further exploration. As a major metropolitan city suffering decades of population loss, Baltimore may have its patterns of population movement strongly influenced by increasing rates of **Black-White** gentrification. Several studies have explored the association between gentrification, residential mobility, and crime in other US cities (Boggess & Hipp, 2016; H. Lee & Perkins, 2023; J. M. MacDonald & Stokes, 2020), with a few focusing on the role of gentrification on population movement and crime (Levy et al., 2020; Phillips et al., 2021; Sampson & Levy, 2020). Future research should consider the possibility that gentrification drives population movement across different neighborhoods based on their ethnic-racial composition. Since residents prefer to travel to neighborhoods with similar economic conditions and racial compositions as their own (Levy et al., 2020; Sampson & Levy, 2020), gentrification may further reinforce their distinct mobility patterns. At the same time, it can lead to shifts in local policing strategies, influencing practices such as direct patrols, stops and arrests, and community-police interactions (Koper et al., 2022; White et al., 2018; Wu et al., 2022).

Finally, I recognize that how residential mobility is measured may heavily influence the relationship between residential mobility and the outcomes examined. Previous studies have indicated that conventional measures of residential mobility may not fully capture the complexities of housing dynamics and population change. In contrast, alternative indicators—such as foreclosure rates or homeowner turnover—may offer a more nuanced and accurate representation of these processes (Boggess & Hipp, 2010; Braakmann, 2023; Cui & Walsh, 2015; Ellen et al., 2013; C. M. Katz et al., 2013). This study does not include these alternative measures, so their potential impact on the findings cannot be assessed. Addressing this limitation will be a key focus of future research, enabling a more comprehensive understanding of residential mobility and its relationship to crime.

Conclusion

Collective mobility patterns should be placed at the center of our efforts to understand crime victimization and social control. Based on the evidence from this study, three key themes emerge. The first theme is that **higher mobility flows are associated with lower crime rates**. After accounting for both resident population and daily visitors to reflect the varying distribution of at-risk populations across neighborhoods, inward and outward population flows contribute to lower crime rates. Aside from the positive relationship between residential mobility and burglary rates, this pattern holds for both robbery and burglary rates across cross-sectional and longitudinal models. This suggests that high population flow functions as a potential source of enhanced guardianship.

The second theme highlights that **intense police activity in neighborhoods creates a strong positive link between mobility and crime.** Since crime hotspots and law enforcement concentrations are closely linked, neighborhoods with high levels of police patrol activities have a complex crime history. These areas may encourage potential offenders to commit crimes, while simultaneously motivating police officers to detect and address criminal incidents, all of which contribute to a strong positive connection between indicators of collective mobility and crime rates.

The third theme is that **mobility-crime connections vary both seasonally and throughout the week**. The varying temporal patterns across different types of mobility flows and crimes suggest that factors such as travel purpose, weather and daylight changes, and crime-specific conditions influence criminal opportunities. These factors can affect the distribution of indoor and outdoor activities, alter the attractiveness of potential victims or properties, and impact security and surveillance levels as part of guardianship. Ultimately, these dynamics influence the extent to which population flows serve as a protective factor against urban crime.

In sum, collective mobility patterns significantly contribute to crime rate changes in Baltimore, and there are substantial variations in their effects across time and space. All of the aforementioned findings highlight the importance of collective mobility patterns within the framework of local crime prevention and public safety—an area that future research should continue to investigate.

Appendix A: Full Regression Tables for Primary Connections

Table A1

Regression results for collective mobility and homicide rates in Baltimore during 2019

Variables[ab]	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Residential mobility	-0.21			-0.15	0.17[+]	0.14	0.14
	(0.16)			(0.14)	(0.10)	(0.11)	(0.10)
Inward population flow		-0.33*		-0.21+	-0.01	-0.04	-0.05
		(0.14)		(0.12)	(0.06)	(0.05)	(0.05)
Outward population flow			-0.27***	-0.22**	0.02	0.02	-0.05
			(0.07)	(0.07)	(0.06)	(0.08)	(0.07)
Disadvantage					0.69**	0.76***	0.68**
					(0.24)	(0.23)	(0.22)
Immigrant prevalence					0.07	0.04	0.07
					(0.13)	(0.13)	(0.12)
African American population					0.43*	0.38*	0.34[+]
					(0.18)	(0.19)	(0.20)
Hispanic population					0.01	0.04	0.05
					(0.11)	(0.13)	(0.13)
Young male aged 15-24					-0.20**	-0.17*	-0.19*
					(0.06)	(0.08)	(0.08)
Housing vacancy					0.27***	0.26**	0.20*
					(0.08)	(0.09)	(0.08)
Renter-occupied housing					-0.06	-0.08	-0.09
					(0.10)	(0.10)	(0.10)
Residential purpose						-0.03	-0.03
						(0.08)	(0.09)

Variables[ab]	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Retail purpose						0.08	0.03
						(0.08)	(0.09)
Industrial purpose						-0.11	-0.15
						(0.08)	(0.10)
Institutional purpose						-0.11^{+}	-0.11^{+}
						(0.06)	(0.06)
Transportational purpose						-0.003	0.01
						(0.04)	(0.04)
Lagged outcome							0.11***
							(0.03)
Number of observations	198	198	198	198	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.

[a] Baseline intercept and selected eigenvectors are not shown in the table.

[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

Table A2

Regression results for collective mobility and robbery rates in Baltimore during 2019

Variables[ab]	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Residential mobility	0.09*			-0.04	0.03	-0.01	0.001
	(0.04)			(0.05)	(0.05)	(0.05)	(0.03)
Inward population flow		0.05^{+}		0.07**	0.05	-0.04	-0.37***
		(0.03)		(0.02)	(0.03)	(0.04)	(0.08)
Outward population flow			-0.22***	-0.25***	-0.14***	-0.10**	-0.05
			(0.05)	(0.05)	(0.03)	(0.04)	(0.04)
Disadvantage					-0.07	-0.01	-0.06
					(0.08)	(0.07)	(0.09)
Immigrant prevalence					-0.05	-0.15^{+}	-0.16*
					(0.09)	(0.08)	(0.07)
African American population					0.19*	0.14^{+}	0.08
					(0.09)	(0.08)	(0.09)
Hispanic population					0.20*	0.28***	0.23**
					(0.08)	(0.08)	(0.07)
Young male aged 15-24					-0.09***	-0.04	-0.05
					(0.03)	(0.03)	(0.04)
Housing vacancy					0.17**	0.17**	0.14**
					(0.06)	(0.05)	(0.05)
Renter-occupied housing					0.12**	0.05	0.04^{+}
					(0.04)	(0.03)	(0.03)
Residential purpose						0.06	-0.02
						(0.07)	(0.07)
Retail purpose						0.25***	0.08^{+}
						(0.06)	(0.05)

Variables[ab]	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Industrial purpose						0.01	0.01
						(0.05)	(0.02)
Institutional purpose						-0.01	0.04
						(0.04)	(0.05)
Transportational purpose						0.03	0.03
						(0.03)	(0.03)
Lagged outcome							0.02***
							(0.003)
Number of observations	198	198	198	198	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.

[a] Baseline intercept and selected eigenvectors are not shown in the table.

[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

Table A3

Regression results for collective mobility and burglary rates in Baltimore during 2019

Variables[ab]	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Residential mobility	-0.08			-0.02	0.11*	0.07	0.08**
	(0.06)			(0.05)	(0.05)	(0.04)	(0.03)
Inward population flow		-0.15+		-0.12+	-0.10	-0.11*	-0.14***
		(0.07)		(0.07)	(0.07)	(0.04)	(0.03)
Outward population flow			-0.11***	-0.08***	0.04	0.03	-0.15**
			(0.03)	(0.02)	(0.03)	(0.03)	(0.06)
Disadvantage					-0.01	0.05	0.02
					(0.12)	(0.08)	(0.06)
Immigrant prevalence					-0.08	-0.11+	-0.05
					(0.08)	(0.06)	(0.03)
African American population					0.18+	0.14	0.17*
					(0.10)	(0.09)	(0.08)
Hispanic population					0.22**	0.23**	0.15***
					(0.08)	(0.08)	(0.04)
Young male aged 15-24					-0.10**	-0.05+	-0.03
					(0.03)	(0.03)	(0.03)
Housing vacancy					0.27***	0.24***	0.13***
					(0.05)	(0.04)	(0.03)
Renter-occupied housing					-0.04	-0.03	-0.05
					(0.04)	(0.03)	(0.04)
Residential purpose						0.01	-0.02
						(0.07)	(0.06)
Retail purpose						0.09*	0.02
						(0.04)	(0.03)

Variables[ab]	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Industrial purpose						-0.04	-0.07
						(0.07)	(0.05)
Institutional purpose						-0.12*	-0.10*
						(0.05)	(0.05)
Transportational purpose						-0.05+	-0.04+
						(0.02)	(0.02)
Lagged outcome							0.01***
							(0.001)
Number of observations	198	198	198	198	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.

[a] Baseline intercept and selected eigenvectors are not shown in the table.

[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

Appendix B: Negative Binomial Regression with MESF

Table B1

Negative binomial regression results for mobility and crime rates in Baltimore

Variables [ab]	**Homicide**	**Robbery**	**Burglary**
Inward population flow	-0.05	-0.40***	-0.17***
	(0.05)	(0.10)	(0.05)
Outward population flow	-0.05	-0.07	-0.15**
	(0.07)	(0.05)	(0.06)
Residential mobility	0.14	0.01	0.07*
	(0.10)	(0.03)	(0.03)
Lagged outcome	0.11***	0.02***	0.01***
	(0.03)	(0.003)	(0.001)
Residential purpose	-0.03	-0.04	-0.02
	(0.09)	(0.07)	(0.05)
Retail purpose	0.03	0.07	0.01
	(0.09)	(0.05)	(0.03)
Industrial purpose	-0.15	-0.004	-0.05
	(0.10)	(0.02)	(0.05)
Institutional purpose	-0.11+	0.02	-0.09*
	(0.06)	(0.05)	(0.05)
Transportational purpose	0.01	0.03	-0.04*
	(0.04)	(0.05)	(0.02)
Disadvantage	0.68**	-0.06	0.03
	(0.22)	(0.08)	(0.05)
Immigrant prevalence	0.07	-0.16*	-0.05
	(0.12)	(0.07)	(0.03)
African American population	0.34+	0.08	0.16*
	(0.20)	(0.09)	(0.08)
Hispanic population	0.05	0.21**	0.16***
	(0.13)	(0.08)	(0.03)
Young male aged 15-24	-0.19*	-0.03	-0.01
	(0.08)	(0.03)	(0.03)
Housing vacancy	0.20*	0.15**	0.14***
	(0.08)	(0.06)	(0.03)
Renter-occupied housing	-0.09	0.03	-0.05

Variables [ab]	**Homicide**	**Robbery**	**Burglary**
	(0.10)	(0.03)	(0.04)
Number of observations	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.

[a] Baseline intercept and selected eigenvectors are not shown in the table.

[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

Table B2

Negative binomial moderation analysis for mobility and homicide rates in Baltimore

Variables [abc]	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Inward population flow	-0.03	-0.03	-0.05	-0.03	-0.04	0.08	-0.04
	(0.08)	(0.05)	(0.06)	(0.09)	(0.08)	(0.10)	(0.09)
Outward population flow	0.02	0.03	0.03	0.02	0.02	0.16	0.02
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.19)	(0.08)
Residential mobility	0.11	0.11	0.10	0.11	0.10	0.26	0.10
	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.22)	(0.13)
Police activity intensity	0.07	0.08	0.05	0.07	0.05	0.19	0.05
	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)	(0.18)	(0.07)
IPF*PAI	-0.01			-0.01	-0.01		-0.02
	(0.08)			(0.09)	(0.07)		(0.09)
OPF*PAI		0.01		0.01		0.15	0.03
		(0.04)		(0.06)		(0.13)	(0.06)
RM*PAI			0.07		0.07	-0.03	0.07
			(0.04)		(0.05)	(0.11)	(0.05)
Number of observations	198	198	198	198	198	198	198

Note. $^{+}p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.

[a] Baseline intercept, selected eigenvectors, and covariates are not shown in the table.

[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

[c] Lagged outcome is excluded, RM=Residential mobility, IPF=Inward population flow, OPF =Outward population flow, PAI =Police activity intensity

Table B3

Negative binomial moderation analysis for mobility and robbery rates in Baltimore

Variables [abc]	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Inward population flow	-0.10*	-0.08	-0.08	-0.10*	-0.11*	-0.09+	-0.10*
	(0.04)	(0.06)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)
Outward population flow	-0.05	-0.06	-0.07	-0.04	-0.05	-0.05	-0.04
	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)
Residential mobility	-0.05	-0.05	-0.04	-0.05	-0.05	-0.05	-0.05
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Police activity intensity	0.20***	0.20***	0.16***	0.21***	0.18***	0.19***	0.20***
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
IPF*PAI	0.05+			0.04	0.05		0.03
	(0.03)			(0.03)	(0.03)		(0.04)
OPF*PAI		0.06		0.04		0.06	0.05
		(0.04)		(0.04)		(0.04)	(0.04)
RM*PAI			0.03		0.02	0.04	0.03
			(0.02)		(0.03)	(0.02)	(0.02)
Number of observations	198	198	198	198	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.

[a] Baseline intercept, selected eigenvectors, and covariates are not shown in the table.

[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

[c] Lagged outcome is excluded, RM=Residential mobility, IPF=Inward population flow, OPF =Outward population flow, PAI =Police activity intensity

Table B4

Negative binomial moderation analysis for mobility and burglary rates in Baltimore

Variables [abc]	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Inward population flow	2.67***	-0.17***	4.04**	-0.23***	-0.22***	-0.17***	-0.23***
	(0.49)	(0.05)	(1.45)	(0.02)	(0.02)	(0.05)	(0.02)
Outward population flow	2.31*	-0.16*	0.85	-0.12+	-0.10+	-0.16*	-0.12+
	(1.12)	(0.07)	(1.14)	(0.07)	(0.05)	(0.07)	(0.07)
Residential mobility	0.86	0.07*	1.50	0.05	0.05	0.07*	0.05
	(1.03)	(0.03)	(1.10)	(0.03)	(0.03)	(0.03)	(0.03)
Lagged outcome	0.45***	0.01***	0.47***	0.01***	0.01***	0.01***	0.01***
	(0.04)	(0.001)	(0.04)	(0.001)	(0.001)	(0.001)	(0.001)
Police activity/hotspot coverage	2.60**	0.01	0.77	0.04	0.06	0.002	0.04
	(0.87)	(0.05)	(0.91)	(0.05)	(0.05)	(0.05)	(0.05)
IPF*PAI	3.63***			0.12***	0.09***		0.11***
	(0.64)			(0.01)	(0.02)		(0.02)
OPF*PAI		-0.05		-0.09+		-0.04	-0.08+
		(0.05)		(0.05)		(0.05)	(0.05)
RM*PAI			0.79		0.03	0.04	0.02
			(1.27)		(0.04)	(0.04)	(0.03)
Number of observations	198	198	198	198	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.

[a] Baseline intercept, selected eigenvectors, and covariates are not shown in the table.

[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

[c] RM=Residential mobility, IPF=Inward population flow, OPF =Outward population flow, PAI =Police activity intensity

Appendix C: Spatial General Additive Modeling (GAM)

Table C1

General additive modeling results for mobility and crime rates in Baltimore

Variables [ab]	**Homicide**	**Robbery**	**Burglary**
Inward population flow	-0.06	-0.38***	-0.11**
	(0.08)	(0.07)	(0.04)
Outward population flow	-0.04	-0.01	-0.10^{+}
	(0.09)	(0.03)	(0.06)
Residential mobility	0.09	-0.06	0.02
	(0.08)	(0.04)	(0.02)
Lagged outcome	0.14*	0.02***	0.01***
	(0.05)	(0.003)	(0.002)
Residential purpose	-0.05	-0.01	0.05
	(0.11)	(0.03)	(0.03)
Retail purpose	0.06	0.10***	0.02
	(0.08)	(0.02)	(0.02)
Industrial purpose	-0.17	0.001	-0.05*
	(0.10)	(0.02)	(0.02)
Institutional purpose	-0.13	0.03	-0.08***
	(0.09)	(0.02)	(0.02)
Transportational purpose	0.01	0.01	-0.06**
	(0.06)	(0.02)	(0.02)
Disadvantage	0.68***	-0.08	-0.01
	(0.17)	(0.05)	(0.05)
Immigrant prevalence	0.08	-0.17***	-0.06*
	(0.14)	(0.03)	(0.03)
African American population	0.30+	-0.002	0.10*
	(0.16)	(0.05)	(0.04)
Hispanic population	0.002	0.19***	0.18***
	(0.14)	(0.03)	(0.03)
Young male aged 15-24	-0.16^{+}	-0.02	-0.03
	(0.09)	(0.02)	(0.02)
Housing vacancy	0.23**	0.06*	0.08**
	(0.08)	(0.03)	(0.03)
Renter-occupied housing	-0.09	0.08*	-0.04

Variables [ab]	**Homicide**	**Robbery**	**Burglary**
	(0.09)	(0.03)	(0.03)
Number of observations	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.

[a] Baseline intercept and spatial interactions are not shown in the table.

[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

Table C2

GAM Moderation analysis for mobility and homicide rates in Baltimore

Variables [abc]	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Inward population flow	-0.04	-0.04	-0.04	-0.03	-0.05	-0.05	-0.03
	(0.09)	(0.08)	(0.08)	(0.10)	(0.10)	(0.08)	(0.10)
Outward population flow	0.04	0.05	0.04	0.04	0.04	0.05	0.04
	(0.09)	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)	(0.09)
Residential mobility	0.05	0.05	0.04	0.05	0.04	0.03	0.04
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)
Police activity intensity	0.11+	0.12+	0.10+	0.12+	0.10	0.11+	0.11
	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
IPF*PAI	0.003			-0.01	0.004		-0.02
	(0.07)			(0.08)	(0.07)		(0.08)
OPF*PAI		0.02		0.03		0.03	0.04
		(0.06)		(0.07)		(0.07)	(0.07)
RM*PAI			0.04		0.04	0.04	0.04
			(0.07)		(0.07)	(0.07)	(0.07)
Number of observations	198	198	198	198	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.

[a] Baseline intercept, spatial interactions, and covariates are not shown in the table.

[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

[c] Lagged outcome is excluded, RM=Residential mobility, IPF=Inward population flow, OPF =Outward population flow, PAI =Police activity intensity

Table C3

GAM Moderation analysis for mobility and robbery rates in Baltimore

Variables [abc]	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Inward population flow	-0.08***	-0.01	-0.02	-0.07**	-0.09***	-0.03*	-0.08***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Outward population flow	0.003	-0.03	-0.03	0.003	0.01	-0.02	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Residential mobility	-0.14***	-0.13***	-0.12***	-0.14***	-0.14***	-0.14***	-0.15***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Police activity intensity	0.18***	0.19***	0.15***	0.20***	0.17***	0.17***	0.18***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
IPF*PAI	0.07***			0.05**	0.06***		0.05**
	(0.02)			(0.02)	(0.02)		(0.02)
OPF*PAI		0.06**		0.04+		0.07***	0.05*
		(0.02)		(0.02)		(0.02)	(0.02)
RM*PAI			0.04*		0.03+	0.05**	0.05*
			(0.02)		(0.02)	(0.02)	(0.02)
Number of observations	198	198	198	198	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.

[a] Baseline intercept, spatial interactions, and covariates are not shown in the table.

[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

[c] Lagged outcome is excluded, RM=Residential mobility, IPF=Inward population flow, OPF =Outward population flow, PAI =Police activity intensity

Table C4

GAM moderation analysis for mobility and burglary rates in Baltimore

Variables [abc]	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Inward population flow	-0.19***	-0.11***	-0.12***	-0.21***	-0.20***	-0.12***	-0.21***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Outward population flow	-0.03	-0.11***	-0.09***	-0.05+	-0.03	-0.10***	-0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Residential mobility	-0.01	0.02	0.01	-0.01	-0.02	0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Lagged outcome	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Police activity intensity	0.07***	0.03	0.02	0.05*	0.06**	0.01	0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
IPF*PAI	0.11***			0.13***	0.10***		0.12***
	(0.02)			(0.02)	(0.02)		(0.02)
OPF*PAI		-0.02		-0.07**		-0.01	-0.06**
		(0.02)		(0.02)		(0.02)	(0.02)
RM*PAI			0.04*		0.04*	0.04*	0.02
			(0.02)		(0.02)	(0.02)	(0.02)
Number of observations	198	198	198	198	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.

[a] Baseline intercept, selected eigenvectors, and covariates are not shown in the table.

[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

[c] RM=Residential mobility, IPF=Inward population flow, OPF =Outward population flow, PAI =Police activity intensity

Appendix D: Regression with Crime Subtypes

Table D1

Analysis for mobility and rates of robbery subtypes in Baltimore

Variables [ab]	Overall	Street Robbery	Commercial Robbery	Carjacking
Inward population flow	-0.37***	-0.39***	-0.31***	-0.26***
	(0.08)	(0.08)	(0.09)	(0.05)
Outward population flow	-0.05	-0.04	-0.13	-0.06
	(0.04)	(0.05)	(0.11)	(0.06)
Residential mobility	0.001	0.01	-0.13	0.09+
	(0.03)	(0.04)	(0.09)	(0.05)
Lagged outcome	0.02***	0.03***	0.11***	0.25***
	(0.002)	(0.002)	(0.02)	(0.04)
Number of observations	198	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.

[a] Baseline intercept, selected eigenvectors, covariates are not shown in the table.

[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

Table D2

Analysis for mobility and rates of burglary subtypes in Baltimore

Variables [ab]	Overall	Residential Burglary	Nonresidential Burglary
Inward population flow	-0.14***	-0.17*	-0.23***
	(0.03)	(0.08)	(0.03)
Outward population flow	-0.15**	-0.17+	0.03
	(0.06)	(0.09)	(0.04)
Residential mobility	0.08**	0.08***	-0.02
	(0.03)	(0.02)	(0.06)
Lagged outcome	0.01***	0.02***	0.03***
	(0.003)	(0.003)	(0.01)
Number of observations	198	198	198

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered-robust standard errors in parenthesis.

[a] Baseline intercept, selected eigenvectors, covariates are not shown in the table.

[b] Except for disadvantage and immigrant prevalence indices, all other predictors are standardized.

Appendix E: Panel Analysis (Monthly Format)

Table E1

Seasonal variations for monthly collective mobility and homicide rates in Baltimore

Variables[abc]	**(1)**	**(2)**	**(3)**	**(4)**
Inward population flow	-0.11	-0.14	-0.10	-0.11
	(0.07)	(0.15)	(0.06)	(0.12)
Outward population flow	0.07	0.08	-0.004	-0.0002
	(0.08)	(0.09)	(0.14)	(0.15)
Summer	0.21	0.20	0.16	0.16
	(0.18)	(0.18)	(0.17)	(0.17)
Fall/Autumn	0.07	0.07	0.07	0.07
	(0.19)	(0.20)	(0.19)	(0.20)
Winter	0.02	0.02	0.02	0.02
	(0.20)	(0.20)	(0.20)	(0.20)
Temporal lag	0.01	0.01	-0.01	-0.01
	(0.16)	(0.15)	(0.17)	(0.17)
IPF*Summer		0.09		0.03
		(0.14)		(0.11)
IPF*Fall/Autumn		-0.01		0.02
		(0.10)		(0.09)
IPF*Winter		-0.06		-0.08
		(0.15)		(0.13)
OPF*Summer			0.27	0.26
			(0.18)	(0.18)
OPF*Fall/Autumn			-0.10	-0.10
			(0.13)	(0.14)
OPF*Winter			0.05	0.07
			(0.20)	(0.21)
Number of observations	2178	2178	2178	2178

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
[a] Clustered-robust standard errors in parenthesis.
[b] Baseline intercept, selected eigenvectors, and other covariates are not shown.
[c] Neighborhood-level fixed effect is excluded in this model due to unreliable standard errors and model convergence issues.

Table E2

Seasonal variations for monthly collective mobility and robbery rates in Baltimore

Variables[ab]	**(1)**	**(2)**	**(3)**	**(4)**
Inward population flow	-0.10	-0.15	-0.10	-0.20
	(0.12)	(0.14)	(0.12)	(0.15)
Outward population flow	-0.06	-0.08	-0.04	-0.06
	(0.13)	(0.14)	(0.09)	(0.09)
Summer	0.31***	0.32***	0.31***	0.32***
	(0.04)	(0.04)	(0.03)	(0.04)
Fall/Autumn	0.19***	0.21***	0.17***	0.20***
	(0.04)	(0.04)	(0.04)	(0.04)
Winter	-0.15**	-0.13*	-0.17*	-0.14+
	(0.05)	(0.06)	(0.07)	(0.08)
Temporal lag	0.0001	0.0001	0.0001	0.0001
	(0.006)	(0.01)	(0.006)	(0.01)
IPF*Summer		-0.01		0.001
		(0.02)		(0.01)
IPF*Fall/Autumn		-0.03+		-0.03*
		(0.01)		(0.01)
IPF*Winter		-0.04**		-0.06**
		(0.01)		(0.02)
OPF*Summer			-0.05	-0.05
			(0.06)	(0.06)
OPF*Fall/Autumn			0.08	0.09+
			(0.05)	(0.05)
OPF*Winter			0.16**	0.19**
			(0.06)	(0.06)
Number of observations	2178	2178	2178	2178

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[a] Clustered-robust standard errors in parenthesis.

[b] Baseline intercept, selected eigenvectors, and fixed effects are not shown.

Table E3

Seasonal variations for monthly collective mobility and burglary rates in Baltimore

Variables[ab]	**(1)**	**(2)**	**(3)**	**(4)**
Inward population flow	-0.13	-0.16	-0.14	-0.16
	(0.10)	(0.12)	(0.09)	(0.12)
Outward population flow	0.07	0.06	0.004	0.01
	(0.18)	(0.17)	(0.17)	(0.17)
Summer	0.15**	0.15**		0.16**
	(0.06)	(0.06)		(0.06)
Fall/Autumn	0.11	0.10		0.07
	(0.08)	(0.08)		(0.07)
Winter	-0.04	-0.04		-0.05
	(0.08)	(0.08)		(0.08)
Temporal lag	-0.004	-0.01	-0.004	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
IPF*Summer		0.003		0.002
		(0.02)		(0.02)
IPF*Fall/Autumn		0.04		0.03
		(0.03)		(0.02)
IPF*Winter		0.003		0.001
		(0.03)		(0.03)
OPF*Summer			-0.03*	-0.03+
			(0.01)	(0.02)
OPF*Fall/Autumn			0.12*	0.11*
			(0.05)	(0.05)
OPF*Winter			0.003	0.01
			(0.06)	(0.06)
Number of observations	2178	2178	2178	2178

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
[a] Clustered-robust standard errors in parenthesis.
[b] Baseline intercept, selected eigenvectors, and fixed effects are not shown.

Appendix F: Panel Analysis (Day-of-the-week Moderator)

Tablet F1

Intraweek variations for daily collective mobility and homicide rates in Baltimore

Variables[ab]	(1)	(2)	(3)	(4)
Inward population flow	-0.09*	-0.05	-0.09*	-0.06
	(0.04)	(0.10)	(0.04)	(0.11)
Outward population flow	0.06	0.07	0.11*	0.10+
	(0.08)	(0.08)	(0.06)	(0.05)
Summer	0.21	0.21	0.21	0.21
	(0.18)	(0.18)	(0.18)	(0.18)
Fall/Autumn	0.08	0.08	0.08	0.08
	(0.19)	(0.19)	(0.19)	(0.19)
Winter	0.004	0.003	0.004	0.003
	(0.20)	(0.20)	(0.20)	(0.20)
Tuesday	0.03	0.03	0.03	0.03
	(0.30)	(0.31)	(0.30)	(0.30)
Wednesday	0.09	0.10	0.09	0.10
	(0.29)	(0.30)	(0.29)	(0.29)
Thursday	0.26	0.27	0.25	0.26
	(0.22)	(0.22)	(0.21)	(0.21)
Friday	-0.09	-0.09	-0.07	-0.08
	(0.21)	(0.21)	(0.20)	(0.20)
Saturday	0.12	0.12	0.12	0.12
	(0.25)	(0.25)	(0.24)	(0.25)
Sunday	-0.20	-0.19	-0.23	-0.22
	(0.21)	(0.21)	(0.18)	(0.19)
Temporal lag	-0.37	-0.37	-0.37	-0.36
	(0.61)	(0.61)	(0.61)	(0.61)
Inward population flow: Tuesday		-0.01		-0.01
		(0.13)		(0.14)
Inward population flow: Wednesday		-0.24		-0.25
		(0.15)		(0.17)
Inward population flow: Thursday		-0.10		-0.13
		(0.08)		(0.10)
Inward population flow: Friday		0.05		0.07
		(0.09)		(0.09)
Inward population flow: Saturday		0.002		-0.001
		(0.13)		(0.13)
Inward population flow: Sunday		-0.09		-0.01
		(0.37)		(0.26)
Outward population flow: Tuesday			0.02	0.02
			(0.15)	(0.14)
Outward population flow: Wednesday			-0.07	0.001
			(0.13)	(0.15)
Outward population flow: Thursday			0.04	0.08
			(0.11)	(0.12)

Variables[ab]	(1)	(2)	(3)	(4)
Outward population flow: Friday			-0.16	-0.18
			(0.17)	(0.18)
Outward population flow: Saturday			-0.0001	-0.002
			(0.11)	(0.11)
Outward population flow: Sunday			-0.29	-0.29
			(0.22)	(0.25)
Number of observations	72072	72072	72072	72072

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[a] Clustered-robust standard errors in parenthesis.

[b] Baseline intercept, selected eigenvectors, and other covariates are not shown.

Tablet F2

Intraweek variations for daily collective mobility and robbery rates in Baltimore

Variables[ab]	(1)	(2)	(3)	(4)
Inward population flow	-0.11*	-0.13*	-0.11*	-0.13*
	(0.05)	(0.05)	(0.05)	(0.05)
Outward population flow	-0.13*	-0.12*	-0.04	-0.03
	(0.06)	(0.06)	(0.07)	(0.07)
Summer	0.31***	0.31***	0.31***	0.31***
	(0.03)	(0.03)	(0.03)	(0.03)
Fall/Autumn	0.20***	0.20***	0.20***	0.20***
	(0.04)	(0.04)	(0.04)	(0.04)
Winter	-0.02	-0.02	-0.01	-0.02
	(0.05)	(0.05)	(0.05)	(0.05)
Tuesday	0.02	0.02	0.02	0.03
	(0.04)	(0.05)	(0.05)	(0.05)
Wednesday	-0.02	-0.03	-0.01	-0.02
	(0.05)	(0.05)	(0.05)	(0.05)
Thursday	-0.09	-0.10	-0.08	-0.10
	(0.06)	(0.07)	(0.07)	(0.07)
Friday	-0.05	-0.07	-0.03	-0.06
	(0.05)	(0.05)	(0.06)	(0.05)
Saturday	-0.004	0.02	0.01	0.03
	(0.07)	(0.07)	(0.07)	(0.07)
Sunday	-0.05	-0.05	-0.04	-0.04
	(0.04)	(0.03)	(0.04)	(0.04)
Temporal lag	0.08***	0.09***	0.08***	0.08***
	(0.02)	(0.02)	(0.02)	(0.02)
Inward population flow: Tuesday		-0.01		-0.01
		(0.01)		(0.01)
Inward population flow: Wednesday		0.01+		0.01**
		(0.01)		(0.01)
Inward population flow: Thursday		0.02*		0.02*
		(0.01)		(0.01)
Inward population flow: Friday		0.02		0.03*
		(0.02)		(0.01)
Inward population flow: Saturday		-0.06**		-0.06***
		(0.02)		(0.02)
Inward population flow: Sunday		0.01		0.01
		(0.02)		(0.02)
Outward population flow: Tuesday			-0.04	-0.04
			(0.04)	(0.04)
Outward population flow: Wednesday			-0.07	-0.07
			(0.09)	(0.09)
Outward population flow: Thursday			-0.06	-0.07
			(0.05)	(0.05)
Outward population flow: Friday			-0.14+	-0.16+
			(0.08)	(0.09)
Outward population flow: Saturday			-0.08	-0.06

Variables[ab]	**(1)**	**(2)**	**(3)**	**(4)**
			(0.05)	(0.05)
Outward population flow: Sunday			0.01	0.01
			(0.05)	(0.04)
Number of observations	72072	72072	72072	72072

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[a] Clustered-robust standard errors in parenthesis.

[b] Baseline intercept, selected eigenvectors, and fixed effects are not shown.

Tablet F3

Intraweek variations for daily collective mobility and burglary rates in Baltimore

Variables[ab]	**(1)**	**(2)**	**(3)**	**(4)**
Inward population flow	-0.21***	-0.21***	-0.21***	-0.21***
	(0.03)	(0.04)	(0.03)	(0.04)
Outward population flow	0.02	0.03	0.03	0.03
	(0.06)	(0.06)	(0.07)	(0.08)
Summer	0.15***	0.15***	0.16***	0.16***
	(0.05)	(0.05)	(0.05)	(0.05)
Fall/Autumn	0.12	0.12	0.12	0.12
	(0.08)	(0.08)	(0.08)	(0.08)
Winter	0.03	0.03	0.03	0.03
	(0.07)	(0.07)	(0.07)	(0.07)
Tuesday	-0.004	-0.004	-0.01	-0.004
	(0.07)	(0.07)	(0.06)	(0.07)
Wednesday	0.04	0.05	0.04	0.04
	(0.06)	(0.06)	(0.06)	(0.06)
Thursday	-0.05	-0.04	-0.07	-0.06
	(0.05)	(0.05)	(0.04)	(0.04)
Friday	0.02	0.02	0.04	0.04
	(0.06)	(0.06)	(0.05)	(0.05)
Saturday	-0.06	-0.05	-0.05	-0.04
	(0.07)	(0.08)	(0.07)	(0.07)
Sunday	-0.28***	-0.27***	-0.28***	-0.27***
	(0.07)	(0.07)	(0.07)	(0.07)
Temporal lag	0.17***	0.17***	0.17***	0.17***
	(0.04)	(0.04)	(0.04)	(0.04)
Inward population flow: Tuesday		-0.02		-0.02
		(0.02)		(0.02)
Inward population flow: Wednesday		-0.01		-0.01
		(0.02)		(0.02)
Inward population flow: Thursday		-0.01		-0.02
		(0.03)		(0.03)
Inward population flow: Friday		0.002		0.01
		(0.02)		(0.03)
Inward population flow: Saturday		-0.08**		-0.07**
		(0.03)		(0.02)
Inward population flow: Sunday		-0.03		-0.04*
		(0.02)		(0.02)
Outward population flow: Tuesday			0.02	0.02
			(0.05)	(0.05)
Outward population flow: Wednesday			0.01	0.02
			(0.04)	(0.04)
Outward population flow: Thursday			0.06	0.06
			(0.06)	(0.07)
Outward population flow: Friday			-0.07	-0.08
			(0.06)	(0.07)
Outward population flow: Saturday			-0.08	-0.05

Variables[ab]	**(1)**	**(2)**	**(3)**	**(4)**
			(0.08)	(0.07)
Outward population flow: Sunday			-0.001	0.01
			(0.07)	(0.07)
Number of observations	72072	72072	72072	72072

Note. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[a] Clustered-robust standard errors in parenthesis.

[b] Baseline intercept, selected eigenvectors, and fixed effects are not shown.

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