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Abstract

There are theoretical reasons to expect that crime opportunities created by the ambient population impact when and where crime occurs. Due to the temporally fluctuating nature of the ambient population, it is necessary to measure it with temporal precision over the hours of the day to assess its relationship with crime. This study uses geo-referenced mobile phone data from Streetlight to create measures of the ambient population over 2-hour time periods across both weekdays and weekends, and assess its relationship with five major types of crime. A proxy for guardianship potential is created based on the percent of the population that voted in the last election. The results indicate that the ambient population is positively associated with all five types of crime measured over nearly all 2-hour time periods. The relationship was particularly strong late at night after midnight, and was particularly strong over most time periods on weekends for robbery. A greater guardianship potential was associated with reduced robberies, burglaries and motor vehicle thefts over all time periods, and with assaults and larcenies in the daytime. The results highlight the importance of measuring the ambient population and guardianship potential, and the temporal variability in their relationships with crime.

Keywords: neighborhoods, crime, ambient population, social control.

Bio

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

Joseph de Leon is an undergraduate student who majored in Data Science at the University of California, Irvine, Donald Bren School of Information and Computer Sciences (Class of 2026). His research interests include spatial analysis, urban planning, and transportation.

Circulating ambient population and crime across the hours of the day:

What role does guardianship potential play?

Recent scholarship has emphasized the importance of measuring the ambient population, and how it is associated with where and when crime occurs (Andresen 2011, Hipp et al. 2019, Malleson and Andresen 2015). The ambient population is a measure of the people at a particular location at a particular point in time, and is distinct from the residential population, which captures where people reside. Thus, the ambient population contains residents inside their homes, residents on the street of their neighborhood, and visitors to the neighborhood. Whereas the ambient population is of interest to many scholars, for many crimes it is these latter two categories—residents outside of their homes and visitors to the neighborhood—that is of most specific interest, as can capture both suitable targets and possible offenders for certain types of crime. We refer to this subset of the ambient population as the circulating ambient population.

A key beneficial feature of some measures of the ambient population is that they provide temporal precision, allowing scholars to estimate the relationship between the ambient population and crime levels at specific times of day. This temporal precision is important for theories that emphasize the temporal co-location between offenders and targets (Felson and Boba 2010, Hipp 2016). Nonetheless, few studies have fully utilized the temporal precision offered by measures of the ambient population to assess the relationship with crime. Whereas some studies have used the temporal precision of ambient population measures to distinguish between crime in the nighttime versus the daytime (Hanaoka 2016, Lee et al. 2020, Liu et al. 2020, Tucker et al. 2021), very few studies have assessed how the ambient population is related to crime across the hours of the day (Hipp et al. 2019, Malleson and Andresen 2015). Given the temporal mobility patterns of persons across the hours of the day, considerable differences exist in mobility patterns even across the various hours during daytime, as well as the various hours during nighttime.

Whereas the ambient population is primarily capturing potential offenders and suitable targets, and thus is expected to be associated with elevated crime levels, a question is whether features capturing potential guardianship in neighborhoods can counteract this effect. For example, the neighborhoods and crime literature posits that neighborhoods with greater levels of collective efficacy are more willing to provide guardianship, and therefore have lower levels of crime (Calder et al. 2025, Sampson, Raudenbush and Earls 1997). Despite the robust evidence consistent with this hypothesis when measuring crime aggregated yearly, further work is needed to understand how collective efficacy operates. For one thing, does the potential increased guardianship uniformly impact crime levels over all hours of the day? And second, can potential guardianship counteract the possible increase in crime that can occur if there is a larger ambient population due to an increase in visitors and residents outside their homes? Whereas a few studies in the ambient population literature have attempted to measure increased guardianship potential by computing the proportion of the ambient population that are local residents, generally finding a negative relationship with crime (Bae et al. 2025, Tucker et al. 2021, Wo et al. 2022), there is limited research attempting to measure the potential of guardianship to impact crime even in the face of a larger ambient population, as well as over the various hours of the day.

In the current study, we exploit the temporal precision of a measure of circulating ambient population to assess how it is associated with crime levels over the hours of the day. We also follow Weisburd and colleagues (Weisburd, Groff and Yang 2012) and construct a measure of the percentage of residents who voted in the last election as a proxy for collective efficacy and increased guardianship potential in the neighborhood. We then assess how this is related to levels of crime over the hours of the day. We also assess how this proxy for guardianship potential operates during hours of the day when there is a particularly large circulating ambient population by testing interactions. In the next section we review the burgeoning literature attempting to measure the ambient population. We describe the various ways the ambient population has been measured, as well as the literature accounting for guardianship potential through proxies measuring collective efficacy or the relative presence of local residents, and the relationship with crime. Following that, we describe our data, and the methods for the analyses. We then present the results, and discuss the findings.

Literature Review

Measuring the ambient population

In recent years, a growing literature has attempted to measure the ambient population. These studies use various strategies, including travel surveys, LandScan data from the USGS, georeferenced social media data such as geocoded tweets or FourSquare check-ins, and geolocations of mobile phone data. These sources have varying degrees of temporal precision, as travel surveys often provide quite limited temporal information over the hours of the day—unless they are combined with simulation techniques (De Nadai et al. 2020)—and the LandScan data typically provides the average ambient population only during the daytime and nighttime, but not with any more temporal precision. The georeferenced social media data is more advantageous in this regard, as it will often have an explicit time stamp. Many of these techniques are increasingly feasible in recent years given the increasing availability of georeferenced mobile phone data, which allows passively capturing the ambient population across various hours of the day.

Whereas some earlier research utilized measures of the ambient population in an attempt to assess whether it better captures the population at risk of crime compared to the residential population, and highlighted the importance of measuring the ambient population (Andresen 2011, Malleson and Andresen 2015), recent research has moved beyond this focus to explore more deeply how the ambient population might be related to crime. Thus, numerous studies have created various measures of the ambient population and assessed how it is related to levels of crime across various geographic units in cities.

As we noted earlier, the ambient population contains three subgroups: 1) residents inside their homes, 2) residents on the street of their neighborhood, and 3) visitors to the neighborhood. We are particularly interested here in the latter two categories, and we refer to this as the *circulating ambient population*. An advantage of measuring the circulating ambient population is that theories such as routine activity theory posit that the ambient population will be related to crime (Felson and Boba 2010). However, a complication is that a larger circulating ambient population implies the presence of not only more offenders and targets, which should increase crime, but also the possible presence of more guardians, if only passive guardians, which would potentially reduce crime. Thus, there is reason to expect a possible nonlinear relationship between circulating ambient population and crime (Hipp 2016). Nonetheless, very few studies have tested for a possible nonlinear relationship.

A body of research has used an estimate of the ambient population over all hours of the day and assessed its relationship with crime levels. Although this strategy does not exploit the temporal precision of some ambient population measures, it nonetheless has demonstrated the general usefulness of measuring ambient population. Whereas research using FourSquare data found a counterintuitive negative relationship between ambient population and several types of crime in New York City census tracts (Kadar, Brungger and Pletikosa 2017), a study using mobile phone data found a positive relationship with larceny-theft (He et al. 2020) and another found a positive relationship with crime in neighborhoods across four cities (De Nadai et al. 2020). A study using Twitter data to measure the ambient population also found a positive relationship with several types of crime (Sypion-Dutkowska et al. 2022), and another found a positive relationship with thefts in Cincinnati neighborhoods (Lan et al. 2019). Thus, these studies aggregating the ambient population over all hours of the day generally find a positive relationship with various types of crime; however, these studies rarely test for a possible nonlinear relationship, which may be theoretically anticipated, nor do they assess whether the relationship varies temporally across the day or night.

An advantage of some measures of the ambient population is that they provide greater temporal precision. Nonetheless, only a limited number of studies have exploited this temporal precision in varying degrees. One body of research has temporally disaggregated the data to distinguish between daytime and nighttime patterns, and assess whether the relationship between ambient population and crime differs during these two periods of the day. For example, a study using mobile phone data in Osaka City, Japan neighborhoods found that increases in the ambient population had a stronger relationship with crime during the nighttime compared to the daytime (Hanaoka 2016), and research using mobile phone data found a positive relationship with crime across four six-hour time periods during the day in Seoul, South Korea (Jung, Chun and Kim 2020). Whereas a study in Great Manchester neighborhoods found a consistent positive relationship between the ambient population and crime across four time periods on weekdays, this relationship was strongest at night in areas with alcohol consumption, which they interpreted as a location with more offenders and potential victims (Lee et al. 2020). Likewise, a study using georeferenced Twitter data found a generally positive relationship between the ambient population of the neighborhood and crime across different time periods of the day for both weekdays and weekends (Liu et al. 2020).

Distinguishing ambient population across the hours of the day

Fewer studies have disaggregated ambient population over all hours of the day. Nonetheless, such a strategy is useful, as studies aggregating data to 6- or 12-hour periods necessarily assumes that the relationship between the ambient population and crime is consistent over that entire time period. Given the temporal mobility of humans, and the theoretical expectations of crime pattern theory, there are reasons to anticipate that the size of the ambient population can change much more frequently than this, and even in hourly time periods (Brantingham and Brantingham 2008). Indeed, routine activity theory posits that it is important to consider the temporal convergence of offenders, targets, and guardians, and therefore greater temporal precision is theoretically appropriate (Felson and Boba 2010). Furthermore, this temporal precision provides better estimates of how the possible composition of offenders, targets, and guardians at a point in time might be related to levels of crime (Hipp 2016).

An early study that utilized the temporal precision of ambient population data focused on the question of the ideal measure of the exposure population for crime (Malleson and Andresen 2015). That is, whereas researchers typically compute crime rates by dividing the number of crime incidents by the residential population, this study posited, and tested, that the ambient population would make a more appropriate denominator when calculating crime rates. Using georeferenced tweets, the researchers created hourly ambient population data in Leeds, UK and found that using the ambient population for calculating crime rates produced stronger results than when using the residential population in the denominator. They found that creating crime rates with the ambient population in the denominator yielded a very different set of crime hot spots compared to using the residential population when computing crime rates.

There is just one study we are aware of that assessed whether the ambient population across various hours of the day was related to crime levels (Hipp et al. 2019). Using geocoded Twitter data over 8 months in the Southern California region, the study was able to aggregate the ambient population to blocks in the region over 2-hour time periods in the day. Furthermore, the study distinguished between weekdays and weekends. There was a positive relationship between the ambient population and five different major types of crime across nearly all hours of the day, both on weekdays and weekends. The strongest results were typically found for aggravated assault and robbery between the hours of midnight and 4am.

Despite these important results, this study did not assess the possible role of guardianship potential of residents in moderating these relationships between the ambient population and crime. Although neighborhoods with more collective efficacy are expected to provide more potential guardianship, research has generally failed to assess whether this impacts crime levels differentially across the hours of the day. We turn in the next section to a discussion of various ways collective efficacy has been measured, including a few studies that have measured the presence of the local population as part of the ambient population, as measures of guardianship potential.

The impact of guardianship potential on crime

Whereas scholars have typically used the ambient population as a potential measure of the presence of more offenders and targets in a neighborhood, measuring the potential for guardianship in a neighborhood is a particularly challenging task. A body of research in the neighborhoods and crime literature has built on social disorganization theory in proposing measuring features of a neighborhood that are anticipated to increase informal social control among residents, which is then expected to translate into greater potential guardianship when needed (Bursik 1988, Sampson and Groves 1989). Building on this literature, Sampson and colleagues (Sampson, Raudenbush and Earls 1997) posited that residents' sense of this potential for informal social control in the neighborhood—what they termed collective efficacy—was a particularly important predictor of actually observing such increased guardianship. They adopted the idea of collective efficacy from Albert Bandura, who defined it as ""the belief in one's capabilities to organize and execute the courses of action required to manage prospective situations" (Bandura 1995: 2). Sampson and colleagues adapted this concept to the neighborhood context and argued that "In sum, it is the linkage of mutual trust and the willingness to intervene for the common good that defines the neighborhood context of collective efficacy" (Sampson, Raudenbush and Earls 1997: 919). A large body of research has thus measured the level of collective efficacy in neighborhoods based on surveying residents and found that it is consistently associated with lower levels of crime (Browning, Feinberg and Dietz 2004, Sampson, Raudenbush and Earls 1997, Wickes and Hipp 2018). One feature of this large body of literature is that it does not consider any temporality of this proposed relationship. That is, these studies typically measure the level of collective efficacy in a neighborhood in some fashion, and then assess whether it is associated with the level of crime over the entire year, over all days and times.

Whereas the most common strategy for measuring collective efficacy in neighborhoods is based on surveying residents (Calder et al. 2025, Sampson, Raudenbush and Earls 1997), there are limitations to this strategy. One limitation is that a relatively large sample size is typically required to obtain a relatively reliable measure of collective efficacy in a geographic unit, and therefore studies have typically been limited to relatively large geographic units, such as census tracts or even pairs of tracts (Sampson, Raudenbush and Earls 1997). A second limitation is the high cost of such a strategy, which has limited the ability to implement it in many settings.

As a consequence of these challenges to measuring collective efficacy, researchers have explored possible proxy variables to capture the level of collective efficacy among residents. One strategy used by David Weisburd and colleagues (Weisburd, Groff and Yang 2012) argued that a measure of voting among residents could be used to capture collective efficacy. The argument built on the insights of political scientists that it is irrational to vote if one only has a simple self-interest, given that one’s singular vote cannot impact nearly any election. Therefore, the motivation for voting is based on altruism (Jankowski 2007) and a sense of the collectivity (Bali, Robison and Winder 2020). Indeed, a study found that those perceiving more neighborhood cohesion were more likely to vote (Gearhart 2020). Consequently, we would expect a neighborhood with more people willing to vote to have greater guardianship potential. In support of this, a study used a measure of the percent voting in the prior election as a proxy for collective efficacy and found a negative relationship with crime across Southern California neighborhoods, although it did not test the possible temporality of this relationship (Hipp 2026).

Another possible proxy for guardianship potential comes out of the ambient population literature, and measures the relative presence of the local population composing the ambient population. In this handful of studies, researchers tend to make a distinction between visitors to a neighborhood and those who live in the neighborhood, with the common presumption that local residents are more likely to behave as guardians compared to visitors. Furthermore, we might anticipate that visitors are more likely to be potential offenders or victims compared to local residents. Given these expectations, we would anticipate that a larger ambient population would increase crime, whereas a larger proportion of local residents would decrease crime. It is also likely important to account for this guardianship potential at specific hours of the day when assessing this possible relationship with crime, although this is rarely done.

A study in Beijing, China found that a higher composition of visitors in the ambient population was associated with larger increases in thefts compared to the presence of residents or employees, with the expectation that they were more willing to serve as guardians (Song et al. 2023). Likewise, a study using mobile phone data in Barcelona Spain neighborhoods found that the presence of more international tourists was associated with more robbery (Valente and Medina-Ariza 2022). Research using Twitter data found that although the ambient population had a positive relationship with both violent and property crime in Los Angeles neighborhoods, a greater presence of local population was associated with reductions in these crimes (Wo et al. 2022). Fewer studies have temporally disaggregated ambient population data to capture the local population. For example, a study using geotagged Twitter data found that a greater presence of local residents in the ambient population was associated with less violence during the daytime on weekdays or weekends (Tucker et al. 2021). Another study of Arlington, Texas neighborhoods measured the proportion of the ambient population who were residents who did not leave the neighborhood, and found a negative relationship between this presumed guardianship measure and burglaries during dinner time and nighttime, but not during breakfast or lunch (Bae et al. 2025). These suggestive results imply that the possible impact of guardianship potential, however measured, may differ over various hours of the day.

Although the presence of more local residents is anticipated to provide more guardianship capability, this is arguably a relatively weak proxy. Although this strategy captures the presence of residents in the neighborhood—as opposed to when they leave the neighborhood—a limitation is that it presumes that all residents are equally likely to provide guardianship. The social disorganization and collective efficacy literatures fundamentally do not assume this, as they instead presume that certain types of persons, in certain types of contexts, are more willing to provide guardianship compared to other residents. For this reason, we adopt the strategy of using a proxy for guardianship potential (or collective efficacy) based on the behavior of residents—their voting behavior. However, we move beyond the existing literature by assessing whether this measure has differential consequences for crime in neighborhoods over the hours of the day.

Summary

As the literature review has highlighted, studies measuring the ambient population have provided some key insights. Nonetheless, few studies have disaggregated the ambient population over the hours of the day. Often, the existing research only aggregates the ambient population to daytime or nighttime periods, which still allows considerable expected heterogeneity in the size of the ambient population during these time periods. Likewise, the collective efficacy literature using various proxies to measure the construct, and its expected guardianship potential, has typically failed to assess the relationship with crime over the hours of the day. The current study extends this existing literature by measuring the circulating ambient population over all 2-hour time periods across both weekdays and weekends. This allows us to assess whether there are key temporal patterns for the circulating ambient population, as well as our proxy for guardianship potential. We next turn to a description of our data and methods.

DATA AND METHODS

Data

This study uses data in block groups (2020 boundaries) in Orange County, CA for the year 2019. We use data before the COVID pandemic given that spatial movement patterns were severely impacted for some time after the onset of the pandemic (Gu et al. 2025). The study site is a relatively large, suburban county. Although Orange County was largely developed in the post-World War II suburban boom, it is a very large area. Our study site has 2,049 block groups with a total population of 3,175,227 persons; we have crime data for 1,537 of the block groups, accounting for a total population of 2,439,178. Although there are about 30 cities in Orange County, the suburban development was such that they have merged together into a single conurbation. Thus, we can effectively treat this study site as a very large city with a population of over 2.4 million.

The data used in this study come from several sources. The crime data come from the Southern California Crime Study (SCCS), and are aggregated to U.S. census block groups in 2020 boundaries. The mobility data come from StreetLight InSight location-based services (LBS) data. Finally, we used data from the U.S. Census American Community Survey (ACS) 5-year estimates for 2017-2021, which are centered on 2019. The data are aggregated to 2-hour time periods across both weekdays and weekends.

Measures

Outcome Variable

Using crime data provided by each police agency, the incidents were coded based on the type of crime, and then geocoded to specific locations and aggregated to the constituent census block group. We created measures from crime incidents during 2019 of aggravated assaults, robberies, burglaries, motor vehicle thefts, and larcenies. For each crime, we determined the day and hour that it occurred, based on what was reported by the victim. Note that there can be temporal uncertainty on the part of victims for some property crimes. We aggregated crime incidents to 2-hour periods over the day (starting at midnight). We also distinguished between weekdays and weekends: weekends were defined as beginning at 6pm on Friday evening and ending at midnight on Sunday.

Key Predictor Variables

Our main variables of interest are based on StreetLight InSight LBS data. We use StreetLight's Zone Activity Volume data source, which estimates the number of trips entering and leaving each Orange County block group based on all modes of travel. This metric is derived from a combination of LBS trips, navigation GPS data, U.S. Census demographics, weather information, road network data, and annual average daily traffic counts derived from permanent traffic recorders. StreetLight uses a Random Forest model calibrated against permanent traffic recorders to extrapolate statistics for the entire population (Streetlight Insight 2019). The algorithm trains a unique model for each month of the year based on spatial and seasonal features. The monthly volume predictions are then validated against 495 permanent counter locations across the U.S. The data capture the number of trips that end at a block group during all hours of the day. We extracted data for all trips during 2019 using all modes of travel.

To calculate the number of people coming to a block group during a 2-hour period we used the data on trip endings from StreetLight. This is our measure of *circulating ambient* *population*. We tested models with both this raw variable, and a log transformed version, and the model fit was always superior using the logged variable, and therefore that is the variable we use in the presented models.

As a measure of guardianship potential, we follow prior research and construct a measure of voting behavior as a proxy for neighborhood collective efficacy (Hipp 2026, Weisburd, Groff and Yang 2012). Using data from the California Statewide Database[1], we compute the proportion of residents registered to vote who voted in the most recent election in 2018. The 2018 election was a local election, and an advantage of using a local election is that this arguably captures more proximate interests on the part of residents, rather than a general election which can capture more national interests. The data collected by the California Statewide Database was apportioned from precincts to blocks, and we aggregated these data to block groups. The denominator is the number of persons registered to vote in the block group.

Analytic Plan

There are 1,537 block groups in our analyses, and given that there was no evidence of overdispersion at any of the time points, we estimated Poisson models for each 2-hour time period over weekdays and weekends for each block group. Thus, there are 84 observations for each block group (12 per day X 7 days), and we adjust the standard errors to account for this. The estimated model is:

$$E(Y) = exp(\alpha + \sum_{h=1}^{H} \beta_1 HR + \sum_{h=1}^{H} \beta_2 AP + \sum_{h=1}^{H} \beta_4 V + \sum_{d=1}^{D} \beta_5 SD) \quad (2)$$

where Y is the outcome of the number of crimes that occurred of a particular type in a 2-hour period for a particular day of the week (aggravated assault, robbery, burglary, motor vehicle theft, or larceny), HR contains dummy variables indicating the 2-hour time period of the day, AP

[1] Available at https://statewidedatabase.org/d10/g18_geo_conv.html.

captures the logged circulating ambient population in a particular 2-hour time period, V is the proportion of residents who voted in the prior election (2018) with a separate coefficient for each time period, and SD is the set of socio-demographic control variables. We tested models with our circulating ambient population measures in the raw metric, or in logged form. We also tested models that included the quadratic versions of the raw or logged circulating ambient population variables to assess nonlinear effects. In all instances, the optimal fit based on the Bayesian Information Criterion (BIC) were the models with logged circulating ambient population, and therefore we present those results. Given the high proportion of zero crime counts, we also tested zero inflated Poisson models; the results for these models were essentially the same as those presented in the main results.[2]

RESULTS

Hourly ambient population patterns

We begin by showing the circulating ambient population measure over the hours of the day in Figure 1A. The two lines show the average size of the circulating ambient population over the hours of the day for weekdays and weekends across block groups. On weekdays (the solid line) there is a smaller circulating ambient population between midnight and 4am compared to weekends. However, beginning at 4am the circulating ambient population begins to rise, and from 4am to 10am there is a larger circulating ambient population on weekdays compared to weekends. From noon to 10pm there are similar circulating ambient population sizes between weekdays and weekends, and then after 10pm there is a larger circulating ambient population on

[2] Note that we do not estimate standard spatial models. This is because our circulating ambient population data already has a strong spatial component to it given the mobility of persons. Including further spatial variables in the model would be atheoretical, and would risk introducing bias into the models.

weekends. From about 8pm on, the size of the circulating ambient population consistently declines on all days.

<<<Figure 1 about here>>>

Hourly crime patterns

We next show the hourly patterns for the various types of crime on weekdays and weekends in Figure 2. In each of these plots we show the percentage of a particular crime type that occurs during that 2-hour period. Thus, for example, the dashed line shows that about 8% of aggravated assaults on weekdays occur between midnight and 2am, 4.6% occur between 2am and 4am, and just 2.8% occur between 4am and 6am. From that point, aggravated assaults increase over the hours of the day and peak near 12.5% between 6pm and 10pm. On weekends (Figure 2B), aggravated assaults are particularly concentrated between midnight and 2am as 13.6% of them occur during this 2-hour window. There are still a large concentration (11%) between 2am and 4am, before dropping after 4am. Beginning at 6am, there is again a slow increase in assaults throughout the day on weekends. On weekdays, the general pattern for robberies (the solid line) is quite similar to aggravated assaults. On weekends, the peak for robberies occurs between 4pm and midnight.

<<<Figure 2 about here>>>

The property crimes differ from the violent crimes of assaults and robberies in that they are more prevalent during daytime hours. Motor vehicle thefts are most prevalent between 6am and 10am, which may also partially reflect when such crimes are detected, and not necessarily when they occur. Larcenies are particularly prevalent during the daytime after 8am, and begin to decline after 6pm, which may reflect shoplifting crimes from commercial establishments during business hours. Burglaries are most prevalent between 8am and 10pm on both weekdays and weekends.

Relationship between circulating ambient population and crime

We next turn to the Poisson regression models in which crime during various 2-hour periods is the outcome variable, and we first focus on the relationship with circulating ambient population. The coefficients for the weekday models are displayed in Table 2. We present the results visually by plotting the coefficients for the logged circulating ambient population variable in Figure 3, and note that all coefficients at all time periods were statistically significant. The left-most clump of bars in Figure 3A show the relationship between logged circulating ambient population and the count of aggravated assaults over the 2-hour periods of weekdays. The strongest positive relationship between circulating ambient population and aggravated assaults occurs between midnight and 2am on weekdays. The relationship is also somewhat strong in the middle of the day between 10am and 6pm. The second clump of bars shows that the positive relationship between circulating ambient population and robberies is strongest in the evening between 4pm and 2am on weekdays.

<<<Table 2 about here>>>

<<<Figure 3 about here>>>

Turning to the property crimes, there are significant positive relationships with circulating ambient population during all hours of the day on weekdays. The relationship between circulating ambient population and burglary (the middle clump of bars) is strongest at night between 8pm and 4am, and is particularly strong between midnight and 4am. The relationship is more moderate during the middle of the day, but still notable. The temporal pattern for motor vehicle theft is a little different, as the strongest relationship with circulating ambient population occurs between midnight and 2am, but the next strongest relationship occurs during the daytime from 10am to 6pm. The relationship between circulating ambient population and larcenies is weakest during the overnight hours from 4am to 8am, but then it consistently strengthens across the hours of the day after 8am. The strongest relationships are in the evening from 4pm to midnight.

We report the coefficients for the weekend models in Table 3, and visually display the coefficients for circulating ambient population in Figure 3B. On average, the relationship between circulating ambient population and these crime measures is stronger on weekends than it is on weekdays. This difference is most pronounced during the overnight hours from 2am to 8am, as the averaged coefficients on weekends are 45 to 55% larger than on weekdays during this time period. On weekends, the strongest relationship between circulating ambient population and aggravated assaults occurs between midnight and 4am, and this is an extremely strong relationship (Figure 3B). The relationship between circulating ambient population and robbery is particularly strong on weekends across most hours of the day. The relationship is particularly strong during the mid-day from 2pm-10pm, as well as from midnight to 2am. But the relationship is still quite strong during other hours.

<<<Table 3 about here>>>

There are temporal differences between circulating ambient population and the three different property crime on weekends (Figure 3B). The relationship with burglaries is quite strong from midnight to 4am, and also rises from 8pm to midnight. However, the pattern for motor vehicle theft is quite different, as there is a relatively strong positive relationship between circulating ambient population and motor vehicle theft during the middle of the day from noon to 4pm, in addition to the late night hours of midnight to 4am. The temporal relationship between circulating ambient population and larcenies is quite pronounced beginning at 2pm into the evening until 4am.

Does guardianship potential have a protective effect?

Whereas there generally appears to be a positive relationship between the circulating ambient population and various types of crime across the hours of the day, a question is whether a greater presence of guardianship potential as proxied by voting behavior by residents can mitigate this pattern to some degree. In Table 3, we see a protective effect for aggravated assault on weekdays during the daytime hours of 8am to 6pm. This is shown in Figure 4A where the strongest negative relationship occurs between 4pm and 6pm, though the relative size of the relationship is similar across the other daytime hours. However, the relationship is not statistically significant in the evening and overnight hours. In contrast, there is a consistent significant relationship between the percent voting variable and robbery across all hours of weekdays. This relationship is quite strong, and relatively similar across all hours of the day.

We also see robust results for the more serious property crimes of burglary and motor vehicle theft, as the relationship is statistically significant over nearly all time periods. For burglaries, the strongest negative relationship occurs in the evening on weekdays between 4pm and midnight. Likewise, there is a strong negative relationship between the percent voting and motor vehicle theft starting at noon, and is particularly strong from 4pm to midnight. The relationship with larcenies is weaker, and only present between noon and 10pm.

On weekends the percent voting has essentially no relationship with aggravated assaults. However, on weekends there is again a relatively strong negative relationship between percent voting and robberies over nearly all hours of the day. This relationship is strongest during the earliest part of the day from 6am to 2pm. The percent voting variable is particularly protective for burglaries during the afternoon into the evening from noon to midnight. Likewise, the percent voting is protective for motor vehicle thefts on weekends between noon and 2am. Again, the percent voting variable has a relatively weak relationship with larcenies on weekends, and is only modestly associated with fewer larcenies in the evening between 4pm and 2am.

Moderating effect of collective efficacy on circulating ambient population

As one final test, we assessed whether our percent voting variable moderated the circulating ambient population variable by creating multiplicative interactions. We found strong interaction effects in the burglary models, but no such pattern for the other crime types. Therefore, we present the burglary interaction models here. We display the coefficient estimates for the interactions in Table 4, and plot a few representative interactions in Figure 5. The lines in these plots show neighborhoods with a high percentage voting (one standard deviation above the mean), an average level, and a low percentage voting (one standard deviation below the mean). The first column of Table 4 shows the interaction coefficients for the weekday models, and the second column shows them for the weekend models. There is a strong negative interaction present in most time periods, indicating that the presence of a higher percentage of voters in the neighborhood mitigates, at least to some degree, the otherwise positive relationship with burglaries that occurs as the circulating ambient population increases. Figure 5A plots the pattern on weekdays between midnight and 2am, and shows that whereas an increasing circulating ambient population is associated with increasing burglaries when there is a low percentage of voters (the top upward sloping line) the increase is less steep in a neighborhood with a high percentage of voters (the bottom line). Thus, in a neighborhood with a large circulating ambient population there is 67% more burglaries in a neighborhood with a low voting percentage versus one with a high voting percentage. We see a similar relationship across nearly all other hours of the day. The gaps between low and high voting percentage neighborhoods for burglaries are 90% between noon and 2pm, and about 200% between 4-6pm or 8-10pm. On weekends, there moderating effects are only observed during daytime hours between 8am and 10pm. Thus, on weekends the gap for burglaries between low and high voting neighborhoods when there is a large circulating ambient population is 100% between 8am and 10am, 230% between noon and 2pm, almost 400% between 4-6pm, and 170% between 8-10pm.

<<<Table 4 about here>>>

<<<Figure 5 about here>>>

Ancillary models

We estimated some additional models to assess the possible nonlinearity for circulating ambient population. First, using a logged version of circulating ambient population in a Poisson model implies a linear relationship (since both are effectively logged). We therefore tested for nonlinear relationships by estimating models that 1) included quadratic versions of the logged circulating ambient population measure; 2) included the raw circulating ambient population variable; 3) included the raw circulating ambient population variable and its quadratic version. In all instances, our models just using the logged circulating ambient population variable showed the best model fit based on the Bayesian Information Criterion (BIC).

DISCUSSION

This study has explored the temporal relationship between circulating ambient population and five different types of crime in block groups across a large metropolitan county. The results have highlighted the importance of distinguishing these relationships with greater temporal precision. In part this is because we showed that the size of the circulating ambient population varies considerably over 2-hour time periods of the day. Furthermore, there was evidence that the relationship between the size of this circulating ambient population and crime varies across the 2-hour time periods. These results highlight the importance of considering the temporality of this relationship. Furthermore, the study also assessed the relationship between the percent of the neighborhood who voted in the last election—as a proxy for collective efficacy and therefore guardianship potential—and crime over hours of the day, and showed that a greater guardianship potential has the expected negative relationship with crime across many hours of the day, with some differences across crime types. These findings are consistent with the possibility that this higher voting percentage has the ability to serve in a guardianship role, although the difference in the benefits across the hours of the day highlights the need for more research on the mechanisms through which such guardianship may operate. We next highlight several key findings.

There was generally a strong positive relationship between the circulating ambient population and crime across most hours of the day (Malleson and Andresen 2016, Song et al. 2023, Tucker et al. 2021). Nonetheless, there were temporal differences in the importance of the circulating ambient population for crime levels. Most notably, the strongest positive relationship between the circulating ambient population and crime occurred between midnight and 2am for most crime types, and across both weekdays and weekends (Hipp et al. 2019, Jung, Chun and Kim 2020, Lee et al. 2020). This larger circulating ambient population is presumably increasing opportunities for crime, and these opportunities are most prevalent during these late-night hours (even sometimes through 4am). This may be because there is more consumption of alcohol during these hours, increasing the proportion of suitable targets among the circulating ambient population (Lee et al. 2020). Another possibility is that the smaller size of the circulating ambient population at this time of night means that there are few potential passive guardians even at locations with a relatively larger circulating ambient population.

Another feature of the circulating ambient population is that it generally had a stronger relationship with crime on weekends (Bae et al. 2025, Song et al. 2023). On weekdays a larger circulating ambient population may, at least to some extent, be an indicator of more workers going to a location. In contrast, on weekends a larger circulating ambient population may indicate more persons engaging in personal activities such as shopping or recreation, which may provide more crime opportunities, consistent with earlier research that did not distinguish between weekdays and weekends (Boivin and Felson 2018). This weekend effect was particularly notable for robberies, as there was a particularly strong positive relationship between the circulating ambient population and robberies on weekends during nearly all hours of the day (Hipp et al. 2019). Future work will want to explore what specific mechanisms bring about this strong relationship between the circulating ambient population and robbery across all hours of the day on weekends.

There were also different temporal patterns in the relationship between circulating ambient population and the other types of crime. Whereas the strongest relationship between circulating ambient population and motor vehicle thefts occurred during the mid-day hours, for burglaries the strongest relationships occur in the evening, and for larcenies the strongest relationships occur during the afternoon hours into the evening hours. Thus, we see differences in how a larger circulating ambient population is related to these different property crimes, and a needed future direction will be to further explore the mechanisms underlying these temporal differences. The violent crime of aggravated assault was different yet: perhaps unsurprising was that a larger circulating ambient population between midnight and 4am was most strongly associated with aggravated assaults, especially on weekends (Hipp et al. 2019). A larger circulating ambient population during these late-night hours likely creates more opportunities for conflict and violence.

One other key finding was testing for temporal differences across the hours of the day in the relationship between a measure of the percent in the neighborhood who voted in the last election (as a proxy for collective efficacy and guardianship potential) and the various types of crime (Hipp 2026, Weisburd, Groff and Yang 2012). Existing research has generally not explored this question temporally, and we found some key differences in this relationship across the hours of the day. For example, the most beneficial effects for the property crimes of burglary and motor vehicle theft were generally found in the afternoon, and especially in the evening, generally starting by 8pm. This greater effectiveness in the evening is consistent with prior research studying burglary and using the percent local population as a proxy for guardianship potential (Bae et al. 2025). The guardianship potential variable had a strong negative relationship with robberies across most hours of the day, although it was weakest after midnight. Likewise, the guardianship potential variable had weak relationships with aggravated assault and larcenies after midnight, raising the need for more research on the possible mechanisms through which such potential guardianship might relate to crime during different hours of the day. If a higher percentage of residents are asleep after midnight, this could explain the weaker late-night effect we observed.

We note some limitations to this study. All measures of ambient population have a degree of uncertainty to them, and ours is no exception. Although Streetlight uses trip transportation data and a machine learning algorithm to expand from their approximately 10% sample, caution nonetheless is warranted. Additionally, the Zone Activity Volume metric is primarily calibrated against vehicular traffic counts, and may not capture foot traffic and transit ridership as well—travel modes that may be relevant to street-level crime opportunities. Although this would be a particularly large limitation in some settings, such as New York City, it arguably is not as pronounced an issue in our study site in southern California. Streetlight may also not capture unusual changes in trip volumes at locations, although the averaging strategy we take across all days of the year mitigates this to some extent since we are focused on typical patterns. Similarly, we do not know the actual composition of the circulating ambient population, so we are unable to measure the composition of offenders, targets, and guardians. We did test for nonlinear effects under the assumption that a larger circulating ambient population provides more potential guardians, but this is a rough proxy. We acknowledge that we focused on the circulating ambient population coming to a neighborhood, and did not focus on whether neighborhoods residents were going to high poverty neighborhoods, despite research suggesting that this has important consequences for neighborhood crime levels (Levy, Phillips and Sampson 2020). This possibility was simply outside the scope of our study design. Finally, our measure of the proportion who voted in the last election as a proxy for guardianship potential is a relatively crude proxy for this construct, and this measurement error should be kept in mind.

Despite these limitations, the results of this study highlight the importance of measuring the circulating ambient population, and how it might be related to the level of crime across the hours of the day. Furthermore, the results highlight the importance of not just measuring the circulating ambient population, but doing so across the hours of the day given that it likely has differential consequences for crime across different time periods. We also showed that a measures of guardianship potential—a proxy for collective efficacy based on voting behavior—appeared beneficial for reducing robbery and serious property crimes during all hours of the day (although more strongly during certain time periods), and larcenies and aggravated assaults during the daytime. Thus, the expected guardianship activity of this measure does not always work uniformly over the hours of the day, which should be a focus of further research. Furthermore, the evidence that the presence of this greater guardianship potential was beneficial in reducing burglaries as the size of the circulating ambient population increases, highlighted the need to combine insights regarding the circulating ambient population along with potential guardianship behavior in neighborhoods to understand when and where crime occurs.

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Tables and Figures

Table 1. Summary statistics of variables in analyses

Circulating ambient population (logged)				
	Weekdays		Weekends	
	Mean	S.D.	Mean	S.D.
12-2am	3.49	0.72	4.20	0.67
2-4am	2.63	0.87	3.20	0.77
4-6am	3.17	1.25	2.82	0.99
6-8am	5.08	1.07	4.17	1.02
8-10am	5.61	0.97	5.29	0.93
10-12pm	5.60	0.90	5.81	0.86
12-2pm	5.88	0.86	6.03	0.81
2-4pm	6.10	0.75	6.02	0.75
4-6pm	6.20	0.70	6.00	0.74
6-8pm	6.09	0.70	5.97	0.74
8-10pm	5.62	0.63	5.65	0.66
10-12am	4.69	0.65	5.03	0.70

Socio-demographic variables		
	Mean	S.D.
Average household income	1.445	0.655
Residential stability	0.000	1.000
Racial/ethnic heterogeneity	0.504	0.164
Percent Black	0.015	0.031
Percent Latino	0.324	0.271
Percent age 16 to 29	0.201	0.102
Income inequality	0.348	0.079
Percent occupied units	0.952	0.072
Population (logged)	7.253	0.509
Proportion voted in 2018	0.670	0.098
Dependent variables		
Robberies	0.011	0.061
Aggravated assaults	0.016	0.076
Burglaries	0.061	0.184
Motor vehicle thefts	0.036	0.121
Larcenies	0.160	0.414

N = 1537 block groups in 2-hour time periods

Table 2. Poisson regression models predicting various types of crime during 2-hour windows on weekdays, using ambient population flow and percent voted in 2018

	Aggravated assault		Robbery		Burglary		Motor vehicle theft		Larceny	
Circulating ambient population (logged)										
Midnight-2am	0.7729	**	0.8254	**	0.9753	**	0.6441	**	0.7158	**
	(9.44)		(9.76)		(13.84)		(10.00)		(16.98)	
2-4am	0.5472	**	0.6266	**	0.7756	**	0.5019	**	0.5762	**
	(7.10)		(8.13)		(16.54)		(6.91)		(15.42)	
4-6am	0.3838	**	0.3257	**	0.4869	**	0.2962	**	0.3007	**
	(6.24)		(5.32)		(17.83)		(8.97)		(13.78)	
6-8am	0.3642	**	0.3039	**	0.4780	**	0.2392	**	0.2776	**
	(6.04)		(3.76)		(15.44)		(9.60)		(15.02)	
8-10am	0.4371	**	0.3989	**	0.5033	**	0.4212	**	0.4145	**
	(7.43)		(6.61)		(15.55)		(13.65)		(23.71)	
10-12pm	0.6520	**	0.5842	**	0.5017	**	0.5424	**	0.5948	**
	(14.87)		(10.78)		(17.52)		(16.90)		(26.53)	
12-2pm	0.5556	**	0.6240	**	0.4919	**	0.6258	**	0.6837	**
	(9.53)		(12.92)		(15.76)		(18.62)		(25.08)	
2-4pm	0.5777	**	0.7720	**	0.5688	**	0.6802	**	0.8179	**
	(11.04)		(12.86)		(13.14)		(16.28)		(22.54)	
4-6pm	0.6444	**	0.8502	**	0.6898	**	0.7627	**	0.9064	**
	(11.22)		(12.67)		(12.66)		(15.94)		(23.83)	
6-8pm	0.5436	**	0.8506	**	0.6491	**	0.5743	**	0.9376	**
	(7.32)		(12.78)		(11.21)		(10.95)		(20.77)	
8-10pm	0.4854	**	0.8686	**	0.8005	**	0.6662	**	1.0877	**
	(6.15)		(11.26)		(12.16)		(10.44)		(17.51)	
10pm-12am	0.6096	**	0.8075	**	0.7574	**	0.4924	**	0.9468	**
	(6.44)		(8.20)		(9.91)		(6.80)		(16.65)	
Percent voted 2018										
Midnight-2am	0.5945		-3.0126	**	-1.8008	**	-3.4634	**	-0.5126	
	(0.94)		-(4.49)		-(4.48)		-(7.42)		-(1.58)	
2-4am	-1.3868	†	-1.8414	*	-0.4182		-3.2615	**	-0.2330	
	-(1.76)		-(2.32)		-(0.91)		-(5.30)		-(0.62)	
4-6am	-0.7504		-2.9793	**	-1.9868	**	-3.0495	**	0.3402	
	-(0.85)		-(3.11)		-(6.44)		-(7.70)		(1.02)	
6-8am	-1.6525	†	-3.8038	**	-2.8878	**	-2.6992	**	0.8726	**
	-(1.94)		-(4.32)		-(10.50)		-(9.90)		(3.76)	
8-10am	-2.0634	**	-3.7632	**	-3.0889	**	-3.1650	**	0.2049	
	-(3.28)		-(6.46)		-(11.79)		-(10.83)		(1.08)	
10am-12pm	-2.2870	**	-4.7718	**	-2.8061	**	-2.4991	**	0.0037	
	-(4.40)		-(9.53)		-(10.85)		-(7.58)		(0.02)	
12-2pm	-1.7646	**	-3.4374	**	-2.4982	**	-3.8945	**	-0.7950	**
	-(3.20)		-(6.78)		-(9.61)		-(11.81)		-(3.82)	
2-4pm	-1.4743	**	-3.4185	**	-2.6509	**	-3.8915	**	-0.9648	**
	-(2.90)		-(6.91)		-(9.84)		-(12.63)		-(4.56)	
4-6pm	-2.8475	**	-3.7887	**	-3.6919	**	-5.2660	**	-1.1143	**
	-(5.78)		-(7.22)		-(11.37)		-(16.78)		-(4.93)	
6-8pm	-0.6219		-4.5750	**	-4.0379	**	-5.2438	**	-1.5181	**
	-(1.19)		-(8.70)		-(11.56)		-(16.64)		-(6.14)	
8-10pm	-1.1964	*	-3.7357	**	-4.2584	**	-5.0199	**	-1.4321	**
	-(2.26)		-(7.02)		-(11.79)		-(13.51)		-(4.55)	
10pm-12am	-0.4809		-1.3427	*	-3.9885	**	-5.2847	**	-0.5609	
	-(0.78)		-(2.08)		-(10.45)		-(14.07)		-(1.53)	

Socio-demographic variables									
Average household income	-0.1861	**	-0.2907	**	-0.2520	**	-0.3308	**	-0.2614	**
	-(4.16)		-(5.43)		-(11.18)		-(11.13)		-(14.93)	
Residential stability	0.0322		0.1053	**	0.1341	**	0.0688	**	-0.0643	**
	(1.52)		(4.37)		(12.25)		(5.11)		-(6.32)	
Racial/ethnic heterogeneity	-0.7749	**	0.1708		0.1988	**	0.1005		0.5098	**
	-(6.25)		(1.24)		(2.72)		(1.28)		(9.81)	
Percent Black	-0.3829		0.4969		0.6226	**	-1.1703	**	-2.1292	**
	-(0.70)		(0.97)		(2.59)		-(3.44)		-(8.85)	
Percent Latino	1.6745	**	1.6560	**	0.9140	**	1.2480	**	-0.0596	
	(16.56)		(13.63)		(17.14)		(19.09)		-(1.22)	
Percent age 16 to 29	-0.1644		0.0916		-0.2490	*	0.1437		0.3437	**
	-(0.86)		(0.45)		-(2.50)		(1.27)		(4.93)	
Income inequality	1.4524	**	1.3680	**	0.6655	**	0.5299	**	0.0561	
	(5.80)		(4.90)		(5.32)		(3.36)		(0.42)	
Percent occupied units	-0.6772	**	-0.6814	*	-0.2603	†	-0.1393		0.0460	
	-(2.71)		-(2.44)		-(1.82)		-(0.83)		(0.49)	
Population (logged)	0.0596		-0.0871	*	0.1325	**	0.2337	**	0.0712	**
	(1.59)		-(2.08)		(6.65)		(9.54)		(4.60)	
Hourly dummy variables										
2-4am	1.9452	*	0.2093		0.4010		0.3011		0.2335	
	(2.31)		(0.25)		(0.90)		(0.49)		(0.56)	
4-6am	1.3122		1.0822		2.0310	**	1.2786	**	0.7898	*
	(1.54)		(1.21)		(5.23)		(2.60)		(2.03)	
6-8am	1.6736	†	1.1162		2.3454	**	1.7668	**	1.0637	**
	(1.94)		(1.23)		(6.19)		(3.87)		(3.02)	
8-10am	1.8265	*	0.9782		2.2489	**	0.8864	†	0.9328	**
	(2.40)		(1.23)		(5.96)		(1.90)		(2.75)	
10-12pm	1.0102		0.9152		1.9386	**	-0.5152		-0.0469	
	(1.45)		(1.23)		(4.99)		-(1.07)		-(0.13)	
12-2pm	1.2570	†	-0.0373		1.5719	**	-0.4793		-0.1394	
	(1.78)		-(0.05)		(3.98)		-(0.99)		-(0.37)	
2-4pm	0.8424		-0.9765		1.1649	**	-0.8590	†	-0.9176	*
	(1.14)		-(1.29)		(2.84)		-(1.75)		-(2.28)	
4-6pm	1.3043	†	-1.2913	†	1.0580	*	-0.5527		-1.4685	**
	(1.84)		-(1.66)		(2.51)		-(1.10)		-(3.57)	
6-8pm	0.7880		-0.6096		1.5782	**	0.7706		-1.4766	**
	(1.02)		-(0.78)		(3.61)		(1.46)		-(3.31)	
8-10pm	1.7419	*	-0.8016		0.9845	*	0.2368		-2.2527	**
	(2.18)		-(0.98)		(2.10)		(0.42)		-(4.06)	
10pm-12am	0.8313		-1.5492	†	1.4268	**	1.5653	**	-1.7125	**
	(0.93)		-(1.70)		(2.61)		(2.68)		-(3.21)	
Intercept	-7.9511	**	-5.5733	**	-6.7310	**	-6.1307	**	-5.5055	**
	-(11.63)		-(7.80)		-(17.05)		-(12.99)		-(16.67)	
BIC	11428.7		9073.84		34763		22912.7		68232.8	

*Note: † p < 0.1; * p < 0.05; ** p < 0.01. T-values in parentheses. N = 87,090 2-hour block group time periods*

Table 3. Poisson regression models predicting various types of crime during 2-hour windows on weekends, using ambient population flow and percent voted in 2018

	Aggravated assault		Robbery		Burglary		Motor vehicle theft		Larceny	
Circulating ambient population (logged)										
Midnight-2am	1.2325	**	1.0230	**	1.0165	**	0.6150	**	0.8830	**
	(8.10)		(7.66)		(10.35)		(6.21)		(11.49)	
2-4am	0.9130	**	0.7937	**	1.0895	**	0.6589	**	0.9206	**
	(8.06)		(5.61)		(10.04)		(5.79)		(10.67)	
4-6am	0.3910	**	0.7707	**	0.7523	**	0.4690	**	0.3796	**
	(3.22)		(7.61)		(11.65)		(5.94)		(7.24)	
6-8am	0.5021	**	0.5851	**	0.6278	**	0.2965	**	0.3875	**
	(5.53)		(4.90)		(11.92)		(5.15)		(11.05)	
8-10am	0.3747	**	0.6241	**	0.6085	**	0.4228	**	0.4863	**
	(3.70)		(5.63)		(12.96)		(8.38)		(13.74)	
10-12pm	0.2690	**	0.8603	**	0.5568	**	0.4634	**	0.5690	**
	(3.04)		(7.90)		(8.07)		(8.99)		(16.14)	
12-2pm	0.4939	**	0.7257	**	0.6509	**	0.7180	**	0.7708	**
	(5.62)		(8.85)		(8.02)		(11.49)		(16.77)	
2-4pm	0.4973	**	0.9697	**	0.6960	**	0.6822	**	0.9070	**
	(6.08)		(10.69)		(5.96)		(11.91)		(15.59)	
4-6pm	0.4816	**	0.9571	**	0.5981	**	0.5463	**	0.9878	**
	(4.75)		(9.90)		(7.69)		(6.83)		(18.50)	
6-8pm	0.4468	**	1.0126	**	0.6977	**	0.5984	**	0.9794	**
	(6.22)		(12.82)		(10.85)		(9.63)		(18.35)	
8-10pm	0.4947	**	1.0670	**	0.7986	**	0.5513	**	1.0315	**
	(6.25)		(10.98)		(10.12)		(7.84)		(16.12)	
10pm-12am	0.5799	**	0.8328	**	0.8203	**	0.5343	**	0.8422	**
	(7.04)		(10.28)		(10.15)		(8.79)		(15.03)	
Percent voted 2018										
Midnight-2am	1.8344	*	-2.9474	**	-3.0938	**	-3.9104	**	-1.5819	**
	(2.03)		-(2.66)		-(4.64)		-(6.00)		-(3.07)	
2-4am	0.6711		0.2044		-1.4544	†	-1.2892		1.1534	†
	(0.76)		(0.18)		-(1.88)		-(1.36)		(1.81)	
4-6am	0.5826		-1.1460		-1.2541	*	-2.7288	**	-0.0077	
	(0.48)		-(0.89)		-(2.05)		-(3.15)		-(0.01)	
6-8am	-1.9789	†	-6.3709	**	-1.8703	**	-2.0711	**	0.9144	*
	-(1.93)		-(4.38)		-(3.23)		-(3.60)		(2.14)	
8-10am	-0.9055		-3.0291	*	-2.5661	**	-1.8550	**	0.4150	
	-(0.91)		-(2.49)		-(5.52)		-(3.97)		(1.14)	
10am-12pm	-0.8269		-4.4320	**	-3.0928	**	-3.1780	**	0.0242	
	-(0.96)		-(3.50)		-(5.62)		-(6.74)		(0.07)	
12-2pm	-1.2184		-4.3498	**	-4.3126	**	-3.6404	**	-0.6126	†
	-(1.58)		-(5.27)		-(7.11)		-(7.04)		-(1.85)	
2-4pm	0.3837		-2.8164	**	-4.3029	**	-4.1127	**	-0.5576	
	(0.49)		-(3.21)		-(5.46)		-(8.62)		-(1.40)	
4-6pm	-0.5171		-2.1899	**	-4.1925	**	-3.8452	**	-0.8307	*
	-(0.51)		-(2.63)		-(7.60)		-(7.59)		-(2.19)	
6-8pm	-0.9565		-3.1208	**	-4.3077	**	-5.0670	**	-1.0673	**
	-(1.60)		-(4.75)		-(9.27)		-(12.56)		-(2.79)	
8-10pm	-1.9877	**	-2.0732	**	-4.0153	**	-4.9029	**	-0.9630	*
	-(3.47)		-(2.86)		-(8.44)		-(11.68)		-(2.42)	
10pm-12am	-0.1948		-2.4326	**	-3.4854	**	-3.8538	**	-1.6924	**
	-(0.33)		-(3.61)		-(7.90)		-(9.24)		-(4.38)	

Socio-demographic variables										
Average household income	0.0191		-0.2069	**	-0.1589	**	-0.2847	**	-0.3255	**
	(0.34)		-(2.64)		-(4.39)		-(6.52)		-(11.26)	
Residential stability	-0.0948	**	0.0627	†	0.1017	**	0.0394	*	-0.0487	**
	-(3.44)		(1.83)		(6.02)		(2.04)		-(2.88)	
Racial/ethnic heterogeneity	-1.0362	**	0.1225		0.3180	*	0.1381		0.4182	**
	-(5.96)		(0.61)		(2.33)		(1.13)		(4.97)	
Percent Black	-0.9837		0.5938		1.3384	**	-0.3680		-1.5872	**
	-(1.41)		(0.72)		(3.70)		-(0.75)		-(4.55)	
Percent Latino	1.8206	**	1.7880	**	1.3555	**	1.6439	**	0.0294	
	(13.21)		(10.04)		(15.26)		(15.96)		(0.37)	
Percent age 16 to 29	-0.4468		0.4422	†	-0.2959	†	-0.3090	†	0.1973	†
	-(1.61)		(1.68)		-(1.83)		-(1.72)		(1.72)	
Income inequality	1.4999	**	1.4464	**	0.6668	**	0.5233	*	-0.3214	
	(4.59)		(3.72)		(3.42)		(2.33)		-(1.40)	
Percent occupied units	-1.1035	**	-0.6856	†	-0.3966	†	-0.5156	*	-0.1842	
	-(3.67)		-(1.75)		-(1.76)		-(2.09)		-(1.29)	
Population (logged)	0.0847	†	-0.1399	*	0.0959	**	0.2293	**	0.0834	**
	(1.65)		-(2.39)		(3.06)		(6.65)		(3.42)	
Hourly dummy variables										
2-4am	2.7972	*	-0.2856		-0.7137		-1.5959		-1.5861	*
	(2.03)		-(0.20)		-(0.88)		-(1.56)		-(1.97)	
4-6am	3.6379	*	0.2951		0.6588		-0.1425		0.9574	
	(2.47)		(0.22)		(0.95)		-(0.16)		(1.30)	
6-8am	4.4463	**	2.7852	†	1.0302		0.6306		0.7749	
	(3.28)		(1.92)		(1.55)		(0.84)		(1.23)	
8-10am	4.1181	**	0.4519		1.3209	*	-0.0994		0.7716	
	(3.11)		(0.32)		(2.12)		-(0.14)		(1.25)	
10-12pm	4.8045	**	-0.0464		1.5726	*	0.2892		0.4325	
	(3.60)		-(0.03)		(2.50)		(0.40)		(0.70)	
12-2pm	3.7661	**	0.9051		1.6414	**	-1.3825	†	-0.5280	
	(2.86)		(0.73)		(2.59)		-(1.79)		-(0.82)	
2-4pm	3.0384	*	-1.4535		1.3043	†	-0.8306		-1.4363	*
	(2.38)		-(1.13)		(1.93)		-(1.10)		-(2.00)	
4-6pm	3.6735	**	-1.5341		1.8986	**	-0.2436		-1.7415	*
	(2.89)		-(1.20)		(2.88)		-(0.30)		-(2.53)	
6-8pm	4.2857	**	-1.2183		1.3624	*	0.2459		-1.5871	*
	(3.45)		-(1.02)		(2.15)		(0.33)		-(2.28)	
8-10pm	4.8293	**	-1.6681		0.7032		0.5669		-1.8151	*
	(3.91)		-(1.31)		(1.06)		(0.74)		-(2.47)	
10pm-12am	3.7111	**	0.2614		0.5888		0.4562		-0.1322	
	(2.95)		(0.22)		(0.84)		(0.60)		-(0.19)	
Intercept	-10.5436	**	-6.7511	**	-6.6882	**	-5.7730	**	-5.6427	**
	-(9.50)		-(5.87)		-(10.34)		-(8.09)		-(9.80)	
BIC	6955.06		4822.61		15524.6		10586.6		29060.7	

*Note: † p < 0.1; * p < 0.05; ** p < 0.01. T-values in parentheses. N = 41,256 2-hour block group time periods*

Figure 1. Circulating ambient population over the hours of the day

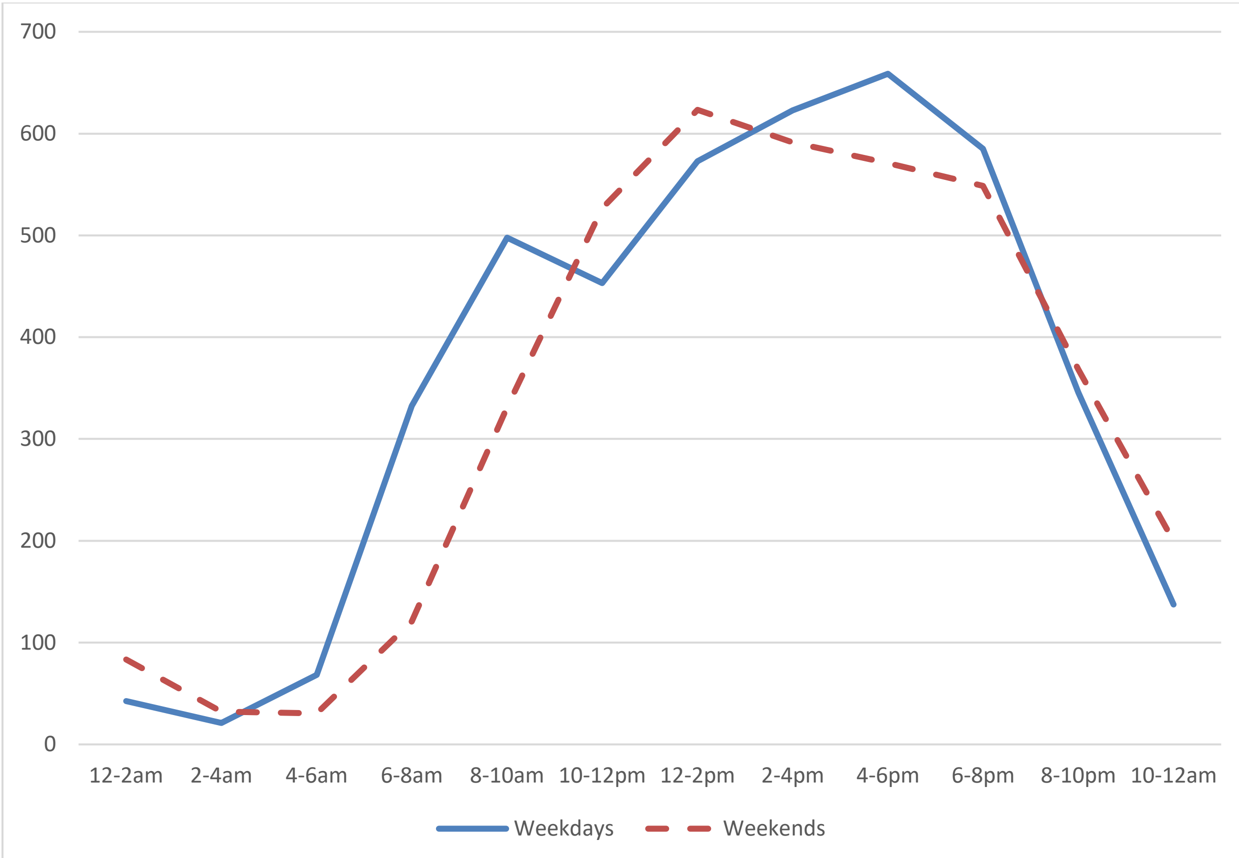

Figure 2. Crime data for hours of the day, split by weekdays and weekends

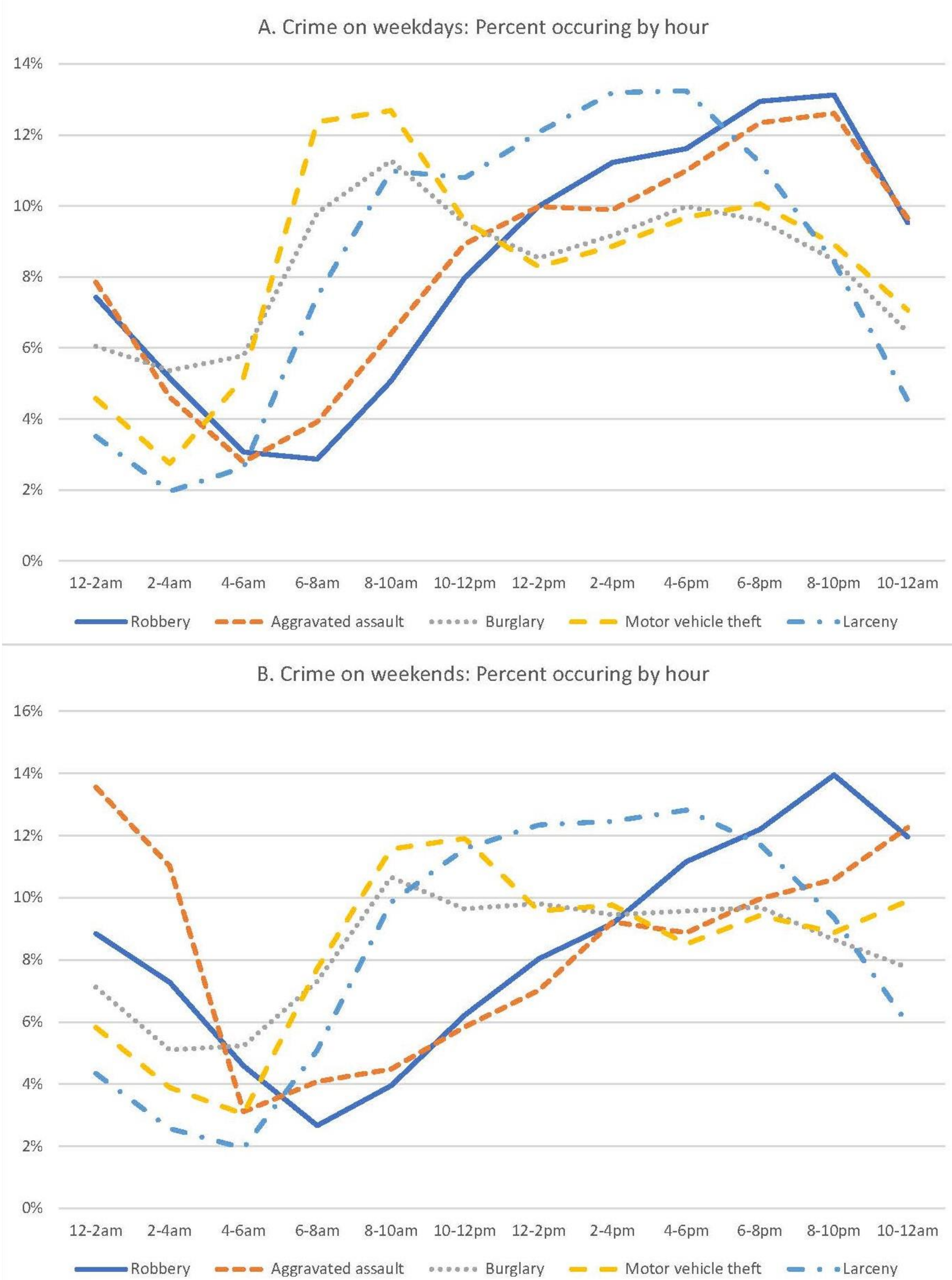

Figure 3. Coefficient values for circulating ambient population and various types of crime, 2-hourly

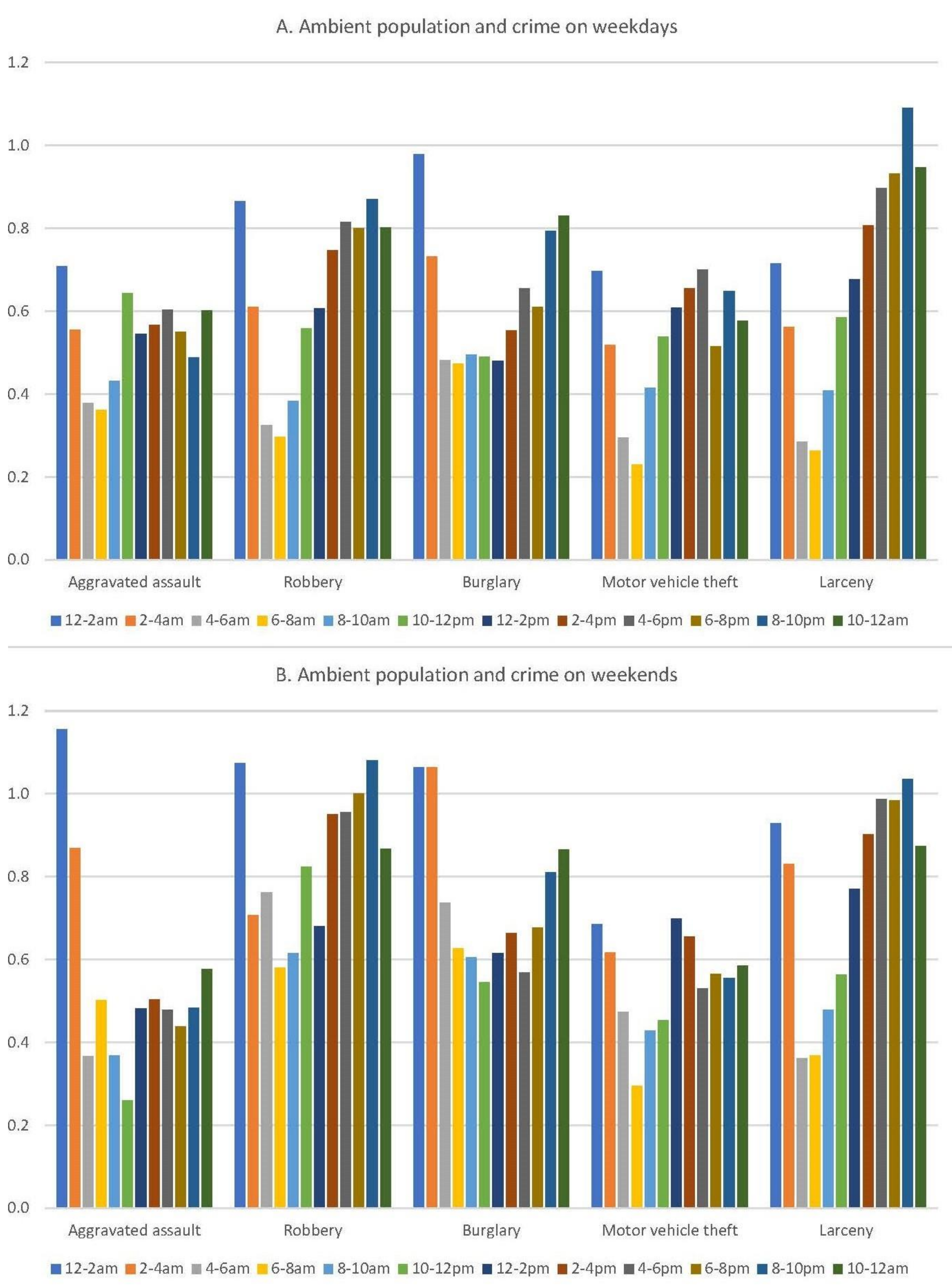

Figure 4. Coefficient values for percent voting and various types of crime, 2-hourly

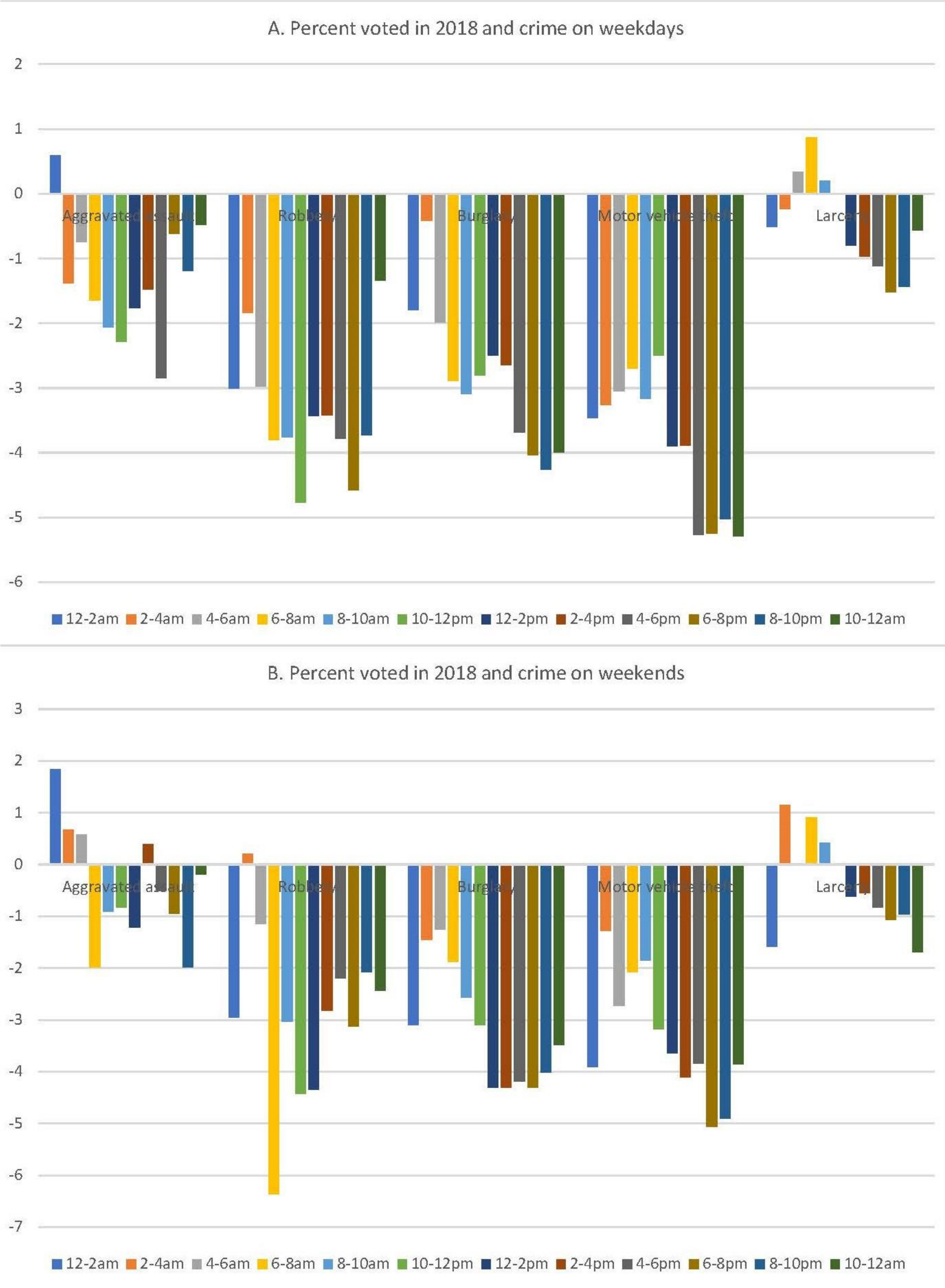

Figure 5. Selected plots for circulating ambient population and percent voting interactions for burglary, 2-hourly