Temporal and Spatial Dimensions of Robbery: Differences across Measures of the Physical and Social Environment

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October 15, 2018

Post-print. Published in Journal of Criminal Justice (2019) 60(1): 1-12

Word count: 9,424

Word count (including references): 10,585

Running Head: "Temporal Dimensions of Robbery"

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Abstract

Objectives: Given the evidence that crime events exhibit both a spatial and a temporal pattern, we explore whether certain social and physical environment characteristics have varying relationships with crime at different times of day.

Methods: We assess this temporal question using a flexible nonlinear parametric approach on a large sample of street segments (and surrounding spatial area) in Southern California.

Results: There are different temporal and spatial patterns for key measures. The presence of total employees in the surrounding area is associated with a reduced robbery risk during the daytime, but not at night. The risk of a robbery is elevated on a high retail segment on weekends during the daytime, and on high restaurant segments into the early evening on weekends. Furthermore, the presence of retail and restaurants in the surrounding area (evidence of shopping districts) was associated with elevated robbery risk in the afternoon and well into the evening.

Conclusion: These different temporal patterns indicate the possibility of different mechanisms in operation.

Keywords: neighborhoods; crime; temporal; spatial.

Bio

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Explaining the Temporal and Spatial Dimensions of Robbery:

Differences across Measures of the Physical and Social Environment

Although a large body of literature has demonstrated that crime is spatially clustered in communities (Boessen & Hipp, 2015; Sampson & Groves, 1989; Weisburd, Bernasco, & Bruinsma, 2009), and a number of studies have described the spatial and temporal distribution of crime (Ratcliffe, 2010, 2012), less research has explored the *covariates* of the temporal patterning of crime (Boessen, 2014; Haberman & Ratcliffe, 2015). Given the temporal rhythms capturing people's movements around the city, along with how crime opportunities flow with these movements, crime naturally exhibits a temporal pattern over the hours of the day and days of the week (Felson & Boba, 2010). This is particularly likely the case for robberies, as they often have a temporal signature given the hours of operation of businesses, or the hours that people are present in public. Despite these well-known temporal patterns, only a limited number of studies have explored whether key features of the physical and social environment are related to crime at locations during particular hours of the day. The few studies that have explored such temporal patterns have typically focused on the relationship between various possible crime attractors (e.g., liquor stores, bars) and levels of crime during particular hours of the day (Haberman & Ratcliffe, 2015). Although such studies provide key insights, and highlight the importance of studying temporal patterns, they typically impose an a priori set of temporal periods in the analysis. In contrast, an important contribution of our approach is to specify and estimate a more flexible parametric temporal model to capture the relationships between these covariates and robberies at different hours of the day, rather than imposing a priori time periods that assume the temporal robbery pattern is constant within each time period.

Although the geometry of crime theory (Brantingham & Brantingham, 1993) and routine activities theory (Felson & Boba, 2010) imply explicit temporal patterns to crime, limited research has studied these temporal patterns. As a consequence, there is little evidence regarding how these temporal patterns may be related to standard covariates of robbery in small geographic units. A challenge for the limited research in this area is how to carve up time when exploring this question. One reasonable approach adopted by Haberman and Ratcliffe (2015) used American Time Use Survey data to determine time periods that exhibited different activity patterns by residents. While this is a useful strategy, it assumes that a particular covariate's effect is constant *within* a time period. We argue that given the relatively unexplored nature of the determinants of robbery in micro locations at various hours of the day—and the fact that the simple presence of people may not be the only determinant of how these relationships change at various time periods (Hipp, 2016)—a more flexible temporal strategy is called for to better understand these possible relationships.

In this paper, we introduce an approach that captures the temporal pattern of the relationship of robbery and various physical and social measures with a flexible nonlinear parametric strategy. This allows us to capture the temporal pattern over which these measures operate, rather than imposing a priori a specific temporal classification scheme (Boessen, 2014; Haberman & Ratcliffe, 2015). This flexible approach is important given the limited existing theorizing regarding the temporal patterns of these measures. We are also able to test whether these temporal relationships differ between measures constructed at the level of the street segment and those constructed in the spatial area surrounding the segment.

Literature Review

Temporal Dimensions of Robbery

A burgeoning crime and place literature focuses on the spatial distribution of robbery, and crime more generally, across micro-units within cities. Much of this literature builds on the theoretical insights of routine activities theory along with crime pattern theory to posit that crime occurs due to the confluence of an offender and a target along with the absence of a capable guardian (L. E. Cohen & Felson, 1979; Felson & Boba, 2010). Although this theoretical perspective implies a precise spatial patterning to crime, and has been studied extensively, it also implies a very precise temporal patterning to crime based on these spatial interactions along with their spatial patterning. However, only a much smaller set of studies have explored this temporal and spatial patterning in combination (Boessen, 2014; Haberman & Ratcliffe, 2015).

Robberies likely have a specific temporal signature given the requirement of a confluence of offenders and targets, along with particular spatial patterns. For example, business robberies can only occur when there are employees at the site, and is typically closely related to the hours of operation of the business. Thus, this will create a distinct spatial pattern of when business robberies can occur. As another example, street robberies require potential targets to be present at various public locations (i.e., streets, parking lots, etc.). To the extent that routine activities of persons shape the times when they are at various locations, this will shape the possible spatial pattern of street robberies. These considerations imply that robberies in general should exhibit particular spatial patterns, and these will likely be further related to the urban morphology of locations (i.e., the presence of various businesses, etc.).

In part this gap in the literature estimating the temporal relationship between various neighborhood characteristics and robbery is due to the acknowledged difficulty of measuring offenders, targets, and guardians at locations at different periods of time. Indeed, a challenge for routine activities theory is first measuring the actual presence of offenders, targets, and guardians at a location at a point in time, and then assessing the relationship between each of these measures and the level of robbery at that place and time point (Hipp, 2016: see page 656). But beyond this challenging problem of identifying these different types of individuals, research has had difficulty even measuring the presence of persons at different periods of time. For example, some recent research has assessed whether measures of the ambient population are related to levels of crime, although these studies typically average levels of crime over all hours of the day (Andresen, 2011; Andresen & Jenion, 2008). There is also some research that has explored whether social media data can be used to capture the presence of an ambient population at specific hours of the day, although social media has uncertain validity (Hipp, Bates, Lichman, & Smyth, 2017; Malleson & Andresen, 2015).

Setting aside the challenge of measuring the specific population at a location at various times of day, a useful approach might be to assess whether certain characteristics of a location (whether socio-structural or physical) have different consequences for the likelihood of robbery events at different hours of the day. The logic is that, given the usual temporal rhythms of a city (Felson & Boba, 2010), certain time-invariant characteristics of a location can regularly imply either more or fewer people at the location on specific days of the week and times of day. Only a few studies have explored whether certain characteristics of a location are related to levels of crime at specific times of day (Boessen, 2014; Haberman & Ratcliffe, 2015). Instead, nearly all existing research simply assesses whether certain characteristics of a location—including the land use characteristics or the socio-demographic characteristics—are related to the level of crime that occurs there (with no distinction between the times of day that such crime occurs). Research therefore usually implicitly averages these effects over the hours of the day. Thus, left unanswered is whether various proxies used in the literature for the presence of offenders, targets, or guardians have differential relationships with crime at various hours of the day, and may have important implications for some of the posited mechanisms.

In the next section, we discuss key measures that have been explored in the ecology of crime literature, how they may differentially capture the presence of offenders, targets, or guardians at various times of day, and how their relationship with robbery may therefore differ over various hours of the day. In part, this consideration follows the suggestions of Taylor (2015) who has emphasized the importance of assessing temporal relationships and considering them theoretically. However, in this study, given the relative lack of existing theorizing and literature regarding the temporal effects of covariates, we refrain from explicitly hypothesizing specific temporal relationships and instead adopt a more inductive approach.

Temporal relationship of covariates with robbery

One bedrock assumption of the ecology of crime literature is that the residential population of an area will be related to the level of crime. Indeed, crime rates are constructed based on this assumption. Thus, studies have tested the relationship between the population of large aggregate units such as cities and crime levels (Hipp & Roussell, 2013), or the relationship between the population density of a neighborhood and the level of crime (Browning, et al., 2010; Sampson & Raudenbush, 1999). Higher population density at a location represents the presence of more potential offenders and targets, and may increase robberies; but also more potential guardians, and may decrease robberies. Nonetheless, even though a count of the residential population in a location is a “time-invariant” measure in that we don’t measure it at different times of the day—in contrast to measures of ambient population that can vary over hours of the day—the *meaning* of the residential population measure differs over the hours of the day. For example, in the daytime it is likely an overestimate of the number of people in the area, as residents often leave the location to go about their daily activities (e.g., going to work, school, etc.) (Boessen, 2014; L. E. Cohen & Felson, 1979; Felson & Boba, 2010). As a consequence, there will be fewer people on the street, providing fewer suitable targets, but there will also be fewer guardians as a result. In the evening, the measure of residential population is likely a relatively good estimate of the number of people in the area and awake—being awake is important for guardianship capability, as well as for being a target for crimes such as robbery. Overnight, the residential population is likely a very good estimate of the number of people in the area; the fact that the residents are more likely to be asleep may indicate that their guardianship capability is quite reduced, however, the fact that there will likely be fewer people on the street implies that there will be fewer suitable targets.

One proxy for the daytime population in an area is the number of employees. This time-invariant measure also has distinct meaning at various hours of the day and days of the week. During the daytime on weekdays this is a measure of the working population in a location, and although these employees can represent a large number of targets in an area for robberies on streets or parking lots, they also can represent a potentially large number of guardians. In the evening on weekdays the area will likely have very few workers present. Whereas this might reduce robbery opportunities given the limited number of suitable targets, the presence of a small number of straggler workers could provide robbery opportunities with few nearby guardians. Overnight, high employee areas typically transform into locations that are effectively empty of people. Although this may make them vulnerable to certain types of property crime, we would not expect them to be vulnerable to robberies overnight. On weekends, such areas would likely have very few of the employees present, and therefore they might operate similar to weekday evenings when the lack of guardians may make the few employees present more vulnerable targets for robbery.

Another set of measures with very time-specific implications are measures of the presence of retail employees or food/restaurant employees. These measures not only capture the presence of locations and employees but also capture the presence of patrons of these stores (as such stores attract customers by design). The temporal patterning of each of these types of businesses is likely relatively regular. For example, retail establishments would presumably have a moderate customer base during the day on weekdays, but perhaps a larger customer base during the evening on weekdays. These establishments would then likely be particularly busy both in the daytime and evening on weekends. This would attract more potential targets, but also potential guardians on the streets and parking lots near them. The extent to which these would serve as crime generators (Brantingham & Brantingham, 1995) likely varies over the hours of the day in a regular pattern. On the other hand, overnight these would be relatively empty locations with few guardians. For business robberies, the hours of operation limit the times when robberies can occur. Furthermore, these businesses may be more attractive targets for robberies during hours when business is slower, as there will be fewer potential witnesses and guardians to robbery events.

Restaurants likely have a particularly precise temporal pattern. Some restaurants are busy in the morning, and many are typically busy during the lunch hour, and again during the dinner hour. However, restaurants typically have fewer customers during the afternoon, and then later in the evening they may have few customers. Overnight, most restaurants will typically be abandoned. These busy times will provide more suitable targets, but also more guardians, for street robberies. On the other hand, the slower business times when the establishment is still open may be more attractive targets for business robberies. These temporal patterns would presumably dictate the temporal pattern of robberies at these locations.

Beyond these more general measures of types of employees, much research in the crime and place literature has focused on the possible role of specific crime attractors in fostering more crime at micro locations (Bowers, 2014; Groff & Lockwood, 2014; Kubrin & Hipp, 2016). For example, studies have looked at the relationship with crime of such possible crime attractors as bars, liquor stores, or vacant units (Bowers, 2014; Groff & Lockwood, 2014). In the case of bars or liquor stores, we would expect a temporal pattern in which they are busy later in the evening and into the early morning hours. This should lead to higher street robbery rates during these hours. It is less clear how much street robberies will be elevated around such establishments during the daytime, as there would likely be few patrons at that time. However, the fewer customers might make them more attractive targets during the daytime for business robberies. Overnight they will likely have few people near them, reducing street robberies, and the fact that they are closed will preclude business robberies. On the other hand, the temporal pattern for vacant units is particularly uncertain: they likely do not attract offenders to them at particular hours of the day. The sole possibility is that in the evening when it is dark, they might provide more robbery opportunities for the offenders who might be present.

Spatial scale

Whereas small geographic units such as street segments are important for understanding the spatial process of crime (Weisburd, et al., 2009; Weisburd, Groff, & Yang, 2012), the movement of offenders requires taking into account the area around the segment as well (Wim Bernasco & Block, 2011; Boessen & Hipp, 2015; Weisburd, et al., 2012). Studies of crime attractor measures, such as bars or liquor stores, have therefore viewed the micro spatial process of nearby street segments (Groff & Lockwood, 2014; Kim & Hipp, 2017). There is likely an even larger spatial footprint when studying retail districts, as they can provide agglomeration effects that are attractive to offenders due to the larger number of potential targets (Teller, Alexander, & Floh, 2016). Likewise, a large industrial area or office park can impact the number of potential targets at such locations.

The broader area around a street segment is also important as the socio-demographic characteristics can impact the number of offenders that might visit the street (Wim Bernasco, 2010a; Wim Bernasco & Block, 2009; Hipp, 2016). Work using egohoods explicitly builds on this notion of spatial patterns, and how the broader urban backcloth can impact the location of robberies (Hipp & Boessen, 2013). Given their small spatial scale, street segments are mostly capturing the presence of suitable targets that are fixed at a location and capable guardians, but not offenders given their typical travel patterns (Wim Bernasco, 2010b; Wim Bernasco & Block, 2009; Rengert, Piquero, & Jones, 1999). The broader meso area is arguably mostly capturing the presence of offenders or capable guardians, and will only capture the presence of targets for crimes such as street robbery to the extent that persons nearby are more likely to be targets and venture to the focal street segment (Hipp, 2016).

Existing research

There currently exists a relatively small body of literature exploring the temporal relationship between various ecological measures and rates of crime. For example, Rengert (1997) found that about 65% of car thefts in central Philadelphia occurred at night time (11:00 p.m. to 7:00 a.m.), a time period in which certain types of businesses are open (i.e., late night bars, theaters). Roman & Reid (2012) found that the density of off-premise alcohol outlets in block groups is positively associated with domestic violence risk during weekdays, but not weekends. Another study (Haberman & Ratcliffe, 2015) first determined certain times of the day and days of the week that have relatively consistent temporal mobility patterns (e.g., weekdays during the daytime when most persons go to jobs) based on time use survey information, and viewed the relationship between various crime attractors and crime over these time periods. Interestingly, they generally detected weak temporal effects for the several crime attractors they studied, although the three measures of social disorganization (concentrated disadvantage, residential mobility, and racial heterogeneity) had coefficients that differed temporally. Another approach defined time periods using a priori reasoning across various time periods of the day, day of the week, and season of the year and estimated separate coefficients across each time period (Boessen, 2014). A recent study explored the spatial and temporal pattern of robbery offenders, and found minimal temporal differences other than for crime incidents near high schools (W. Bernasco, Ruiter, & Block, 2017).

Whereas this existing research has provided key insights, we propose an alternative strategy that more flexibly estimates the temporal patterns between various socio-demographic characteristics and robberies. A necessary assumption of the existing strategies of defining a priori time periods is that the covariates operate in a consistent fashion *within* these time periods. In our approach, rather than attempting to identify particular time periods a priori in which measures may operate differently for crime, we instead adopt an empirical approach in which we parametrically estimate the relationship between various measures of interest and crime rates at different times of day. Our more flexible approach allows the size of the coefficients to change in a systematic fashion over the hours of the day, rather than assuming specific periods when they operate in a particular fashion. We accomplish this by estimating the parameters for these variables of interest as a nonlinear function of the hours of the day. Furthermore, we estimate these temporal patterns separately for weekdays and weekends given the likely differences in the temporal patterns on weekends.[1]

Data and methods

Data

Dependent variables

The robbery data for this study come from the Southern California Crime Study (SCCS). In that study, the researchers made an effort to contact each police agency in the Southern California region (the five counties of Los Angeles, Orange, Riverside, San Bernardino, and San Diego) and request address-level incident crime data for the years 2005-2012. Many of the agencies were willing to share their data. As a consequence, there is crime data covering about 83.3 percent of the region's population. We used robbery data averaged over 2009-11. Note that computing the mean, as we do here, yields identical results to computing the sum over these three years (just with a different intercept). The data come from crime reports officially coded and reported by the police departments. For this study, we classified crime events that were reported as robberies, given that robberies are the crime type typically reported with the most temporal precision. Robberies were geocoded for each city separately to latitude–longitude point locations using ArcGIS 10.2, and located to street segments. The average geocoding match rate was 97.2% across the cities, with the lowest value at 91.4%. For the 2.2 percent of events at intersections we evenly randomly assigned them to one of the contiguous street segments, as described in more detail below. These crime data have been used in several prior studies (Kubrin & Hipp, 2016; Kubrin, Hipp, & Kim, 2016).

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[1] Note that in principle we could also estimate separate coefficient patterns for each of the seven days of the week. However, empirical exploration of this idea in early models with our sample indicated that we can safely collapse the data to just "weekday" and "weekend" and appropriately capture the temporal variation in the data.

Temporal Dimensions of Robbery

Given that we have the time and date of robbery events, we classified each event into one of 12 2-hour time periods for a day: midnight-2am, 2-4am, 4-6am, etc. This is the greatest temporal precision we can use, as crime events were too sparse in one-hour periods to estimate the models. Thus, the outcome measure is whether or not a robbery event occurred within a 2-hour period. We also distinguished between weekdays and weekends, given the typically different spatial and temporal patterns of people within the city. We defined the weekend as starting at 6pm on Friday, and continuing until midnight on Sunday. The remaining time was classified as weekday.

Independent variables

We constructed a set of variables aggregated to the street segment. These measures are all time invariant. To capture the presence of employees and patrons of businesses we used the Reference USA (Infogroup, 2015) data for 2010. The Reference USA data provides point-level information, allowing us to geocode these businesses and place them precisely on the appropriate segment. We constructed several measures (each log transformed). To capture locations populated by workers in general, we constructed a measure of *total employees* (all workers). We captured locations with workers who attract the public as customers with measures of 1) *retail employees*; 2) *restaurant employees* (these represent not only the workers, but proxy for the presence of customers as well). We constructed two measures that might attract offenders, or "crime attractors" as 1) *bar employees*; 2) *liquor store employees*. Note that these measures of employees in specific industries overlap with the total employee measure, and therefore to properly interpret the total effect of a change in, say, restaurant employees one would need to combine the restaurant employee and total employee coefficients. We also constructed a measure of the proportion of land in the segment constituting *vacant land* using parcel land use data obtained from the Southern California Association of Governments.

We constructed measures of the socio-demographic characteristics of segments. For the data from the U.S. Census, we needed to apportion data aggregated to the block to the constituent segments. We followed the simple average approach of Kim (2018) that accounts for the residential population in each block adjacent to a segment, as his work showed that this approach performs similarly to more complicated imputation strategies. In this approach, 1) the information for each block is equally apportioned to all segments that are adjacent to the block; 2) for each segment, the information from each block that is adjacent is averaged to compute estimates at the segment level. To capture the presence of residential population we included a measure of segment *population (logged)*. We included several measures capturing the socio-demographic characteristics of residents. We constructed a measure of *concentrated disadvantage*, as a factor analysis of four variables: percent at or below 125% of the poverty level; average household income; percent with at least a bachelor's degree; percent single parent households, and then computed factor scores from this analysis.[2] A measure of *residential stability* combines standardized values of percent owners and average length of residence. We captured the racial/ethnic composition with measures of *percent black*, *percent Latino*, and *percent Asian* (with percent white and other as the reference category). We measure *racial/ethnic heterogeneity* with a Herfindahl index of five groups (percent white, black, Asian, Latino, and other race). We measure the crime generating possibilities of vacant units with the

[2] Given that only the percent single-parent households variable is available for blocks, we use synthetic estimation for ecological inference as described by Boessen and Hipp (2015) to impute the other variables (M. L. Cohen & Zhang, 1988; Steinberg, 1979). Variables used in the imputation model were: percent owners, racial composition, percent divorced households, percent households with children, percent vacant units, population density, and age structure (percent aged: 0-4, 5-14, 15-19, 20-24, 25-29, 30-44, 45-64, 65 and up, with age 15-19 as the reference category).

percent vacant units. To capture the crime-prone population (Sampson & Laub, 1993) we follow prior scholars and measure the *percent aged 16 to 29* (Kubrin & Hipp, 2016).

To capture spatial effects, we also constructed spatially lagged measures of the business and Census variables just described. These were constructed as an inverse distance decay of the area surrounding a segment based on Euclidean distance, row standardized, and capped at ½ mile such that more distant segments are weighted zero. There was no evidence of spatial autocorrelation of the residuals in our models. The summary statistics for the variables used in the analyses are shown in Table 1. Given that we are using such fine grained time periods, despite the fact that there were nearly 33,000 robberies, fully 99.76% of the time periods did not experience a robbery.

<<<Table 1 about here>>>

Methods

Whereas the few existing studies looking at spatial/temporal patterns have typically estimated a separate model for each time period, we adopt an approach in which we estimate the time periods simultaneously as a single model. Thus, the common approach in the literature that defines time periods a priori, and then estimates the model separately for each time period, assumes that there is no temporal variation for a coefficient *within* a particular time period, but only allows for variation in a coefficient *across* the time periods. Thus, for a hypothetical variable this approach might estimate a smaller coefficient during the day (e.g., β=1.2) and a larger one in the evening (e.g., β = 3.0). However, the break point between day and evening is typically not certain. Furthermore, a consequence of this modeling strategy is that it results in the implausible assumption that the coefficient is indeed 1.2 in the hour before the break point but then 3.0 in the hour afterwards. It seems unlikely that there would be such a dramatic difference in the coefficient, especially given that the uncertainty regarding when this break point actually occurs. Instead, we argue that it is more plausible that the coefficient slowly changes over the hours of the day in a more continuous fashion (rather than such a sharp discontinuity, as is posited in the approach creating time periods).

Therefore, our strategy takes a different approach in that it only constrains the coefficients to be equal within the smaller two hour periods, and allows them to vary across those periods. Furthermore, given that we would expect the effect of variables on robbery to change in a systematic fashion over the hours of the day, our approach parametrically constrains the temporal change of these parameters. We tested several functional forms of this temporal change to minimize the possibility of an incorrect constraint on this temporal change. We found that a cubic function satisfactorily captured this temporal change in our sample.

Thus, we parameterize the time effect in these models by creating a variable with values capturing the specific 2-hour periods (0=midnight-2 a.m.; 1=2-4 a.m.; 2=4-6 a.m., etc.). Given that we expect the effects to change in a nonlinear fashion over the hours of the day, we also constructed quadratic and cubic measures of this time variable. Furthermore, we created two different sets of linear, quadratic, cubic hourly variables: one for weekdays, and one for weekends, and thus created a set of 6 time variables (the weekday hourly variables have values of 0 for weekend observations, and vice versa).

To assess whether the relationship between specific variables and robberies changes over the hours of the day we constructed interaction variables between each variable of interest and our set of six time variables. For each variable of interest, we estimated a model in which these six interaction variables were included in the model. We included these interactions in separate models for each variable of interest, as including them simultaneously would require extremely complex interpretations of the interactions (given that the interactions could not be interpreted separately holding constant the other variables in the model).

Given that we split the robbery incident data into very small 2-hour temporal bins (and split it as well between weekdays and weekends), the count in any particular cell rarely exceeds 1 (just 0.02% have more than one crime incident). Therefore we reclassified this as a 0/1 variable and estimated logit models. We account for the nesting of these 2-hour bins within particular street segments by adjusting the standard errors for clustering.[3] Given the uncertain location of crimes at intersections, we created five imputed datasets of random assignment to segment, estimated the models on each, and corrected the standard errors when combining the results to appropriately account for the uncertainty (Rubin, 1976).

We can write the estimated equations as:

$$\Pr(y_t = 1 \mid \mathbf{X}) = F(\alpha + \beta_1(H_{WD}) + \beta_2(H^2_{WD}) + \beta_3(H^3_{WD}) + \beta_4(H_{WE}) + \beta_5(H^2_{WE}) + \beta_6(H^3_{WE}) + \beta_7(WE) + \beta_{11}(x_1{*}H_{WD}) + \beta_{12}(x_1{*}H^2_{WD}) + \beta_{13}(x_1{*}H^3_{WD}) + \beta_{14}(x_1{*}H_{WE}) + \beta_{15}(x_1{*}H^2_{WE}) + \beta_{16}(x_1{*}H^3_{WE}) + BX)$$

where y_t is 0/1 whether a robbery occurred in a particular time period, H_{WD} is the hour variable on weekdays (with coefficients β_1, β_2, and β_3 capturing the main effect, quadratic, and cubic effects, respectively), H_{WE} is the hour variable on weekends (with coefficients β_4, β_5, and β_6 capturing the main effect, quadratic, and cubic effects, respectively), WE is a dummy variable for weekend time periods, $x_1{*}H_{WD}$ is an interaction between the variable of interest (x_1) and the

[3] An alternative approach would estimate the models as multilevel logit models in which level 1 is the particular time period and level 2 is the segment. However, it was not feasible to estimate such models given the size of the dataset and model. When attempting to estimate the models, they were taking extremely long periods of time (over multiple days, and longer), and were not able to reach satisfactory convergence even when increasing the number of quadrature points in SAS. Another strategy would estimate these as multilevel linear models, but such models would ignore the 0/1 nature of the outcome variable; furthermore, such models are particularly inappropriate when the outcome variable occurs relatively rarely, as is the case here. But we do not need to use rare event logit, as it is the number of events (of which we have many), and not the proportion, that determines the need for rare event logit models (http://statisticalhorizons.com/logistic-regression-for-rare-events).

hour variable on weekdays with a β_{11} effect on robberies in that time period (and β_{12} and β_{13},capture the quadratic and cubic effects of weekday hours when interacted with this variable of interest), x_1*H_{WE} is an interaction between the variable of interest (x_1) and the hour variable on weekends with a β_{14} effect on robberies in that time period (and β_{15} and β_{16} capture the quadratic and cubic effects of weekend hours when interacted with this variable of interest), X is a matrix of the control variables and B is the matrix of coefficients capturing their effects on robberies in a particular time period.

Results

We first display the results from the main effects model that does not include interactions between any of our measures of interest and the hourly variables (the complete set of coefficient estimates from this model are shown in Table A1 in the Appendix). The hourly results from this model are plotted in Figure 1 and demonstrate that there is a pronounced pattern of robberies over the hours of the day for both weekdays and weekends. For this and all other figures we plot the predicted value of the presence of a robbery during each 2-hour period. We see that robberies increase during the day and peak from about 4-8pm on weekdays and from 8-10pm on weekends, controlling for the variables in the model. On weekends, the robbery risk remains relatively high from 12-4am, but it is not elevated on weekdays during these late-night hours.

<<<Figure 1 about here>>>

We next turn to the interactions with our variables of interest and begin with the relationships between the total number of employees in the segment and the surrounding area over various hours of the day (all coefficient estimates for the interactions and statistical significance are shown in the Appendix Table A2). We summarize the results showing the time period of the strongest temporal effects for each measure in Table 2. Figure 2a displays the relationship between the number of total employees on a segment (the three lines showing segments with low, medium, and high numbers of total employees) and the predicted probability of a robbery (the y-axis) on weekends over the hours of the day (the x-axis); the plot for weekdays is not shown given that the interactions were not statistically significant. This plot shows that whereas the gap between the lines is narrowest between 4 and 10am, they widen after this point and therefore total employees has the strongest positive relationship with robberies in the daytime from about 10am to 6pm. When viewing the relationship between the number of total employees in the surrounding area and robberies over the day for weekdays (Figure 2b) or weekends (not shown, but significant) we observe very different patterns compared to the segment measures. For one thing, there is actually a *negative* relationship between the total number of employees in the surrounding area and the number of robberies on a segment (given that the "high" line is lowest in this figure). However, this pattern is very temporally determined: on weekdays the negative relationship with nearby total employees becomes pronounced starting around 6am and peaks from noon to 6pm: the odds of a robbery event on a segment surrounded by many employees are nearly 30% of those on average segments (from noon to 2pm the odds are .014143 on a segment surrounded by high total employees and .01979 on one surrounded by average total employees).[4] On weekends, this protective effect of many total employees in the surrounding area is shifted a little later, from about 10am to 6pm, in which the odds of a robbery event on a segment surrounded by many employees are 60% of those on average segments. However, this protective effect appears to evaporate late at night, highlighting the unique temporal pattern of robbery in high employment areas.

[4] Note that whereas these may appear to be quite small probabilities, this is because we have sliced the data into such thin time slices. For this reason, the odds ratios accurately capture the increase in robbery risk in such narrow time periods.

Temporal Dimensions of Robbery

<<<Table 2 about here>>>

<<<Figures 2a and 2b about here>>>

Turning to the temporal pattern for the measures of retail employees, although there is always higher probability of a robbery in segments with more retail employees regardless of the time of day, this effect (based on the wider gap in the lines) is more pronounced in the afternoon from 10am to 6pm on weekends (not shown, but significant and similar to Figure 2a). During the late afternoon, the odds of a robbery on a high retail employee segment are about 35% higher compared to an average segment. These interactions were not statistically significant in segments on weekdays. When looking at the number of retail employees in the surrounding area (capturing high retail environments), we observe particularly strong temporal patterns. On weekdays, the positive relationship with nearby retail employees becomes particularly strong starting after 10pm and continuing until almost 4am (Figure 3a). The increased odds of a robbery on these segments on weekdays range from 16% between 10am-2pm to 60%-165% between 8pm-midnight. The pattern is similar on weekends, except that the positive relationship with nearby retail employees is particularly strong at night from 10pm to almost 4am (Figure 3b). These areas likely have few pedestrians at these hours, and the odds of a robbery are increased between 60% and 110% during these hours.

<<<Figures 3a and 3b about here>>>

We expected restaurants to act as crime generators, similar to retail establishments, except that their temporal patterns may be later in the evening. We find that street segments with more restaurant employees indeed have increased robberies on weekends from about noon to 6pm (Figure 4), but the interactions are non-significant on weekdays. The increased odds of a robbery on these segments on weekends are over 20% between noon-6pm, but effectively zero from 10pm-midnight. There is an even more pronounced temporal pattern for street segments that have many restaurants in the surrounding area: a segment with more restaurant employees in the surrounding area experiences higher probability of a robbery on weekdays from about 8pm to 4am (similar to Figure 3a), and a bit later on weekends from 10pm to 6am (similar to Figure 3b). These are strong effects, as the increased odds of a robbery on such segments over the hours of the day range from 0 to 78% on weekdays, and from 21% to 50% on weekends.

<<<Figure 4 about here>>>

We also see evidence of temporal patterns based on the size of the residential population. During weekends, segments with more population experience a larger uptick in robberies between 6pm and 4am than segments with smaller population (Figure 5). Whereas high population segments have 40-50% higher odds of a robbery during the middle of the day, these odds rise to 85% to 215% between 6pm and 4am. So residential population is related to increased robberies in the evening on weekends when people are more likely to be around. The temporal differences are not statistically significant on weekdays, and there are no significant temporal effects of population in the surrounding area.

<<<Figure 5 about here>>>

We next turn to the crime attractor measures: bars, liquor stores, and vacant units. We find that the effects for these measures are generally quite localized to the segment. For bars, the size of the effect is somewhat modest (based on the gap between the lines), although it does peak between midnight-6am on weekdays (significant, but not shown) and on weekends (the increased odds range from 5% to 31% on weekdays and from 0% to 28% on weekends over the hours of the day). Notably, the size of the effect is strongest between midnight and 2am regardless of day of week. The relationship between the number of bars in the surrounding area and robberies in the segment is also somewhat modest, although it is strongest between 10pm and 4am on weekends. Although the relationship of liquor stores with robberies does not significantly vary over the day on weekends, it does exhibit the strongest relationship between 8pm and 4am on weekdays. Whereas the heightened odds of a robbery on such segments are 16% in the afternoon, it is 73% between 10pm-midnight. The number of liquor stores in the surrounding area is not related to the number of robberies, as we anticipated. The temporal pattern of our other "crime attractor", vacant units, is slight as there is no evidence of temporal pattern on the street segment.

Socio-demographic control variables

We find that the protective effect of residential stability on robberies is strongest in the afternoon into the evening (from about 8pm to 4am) on weekdays (significant, but not shown). Although we did not explicitly theorize this, it may be that the greater informal social control on such segments is most activated when residents are in the area and active (i.e., the afternoon and evening). Whereas the odds of a robbery are about 10% lower on a high residential stability segment in the middle of the day, they are 18% to 33% lower in the evening. The temporal pattern was similar on weekends, although not statistically significant. When viewing the residential stability of the surrounding area, we see the unexpected result that higher levels of stability actually are associated with higher robbery levels on the segment; this pattern is strongest on weekdays between about 8am and 6pm, but effectively disappears overnight. The pattern is similar on weekends. Thus, residential stability as a protective factor appears to operate in a more micro fashion, consistent with some prior research (Boessen & Hipp, 2015; Hipp, 2007).

Temporal Dimensions of Robbery

Although we do not detect a temporal pattern for concentrated disadvantage, we do observe a temporal pattern for racial/ethnic heterogeneity at the segment level. Robberies are more frequent on high disadvantage segments, and segments surrounded by high disadvantage, regardless of the time of day. We observe a temporal pattern for racial heterogeneity in which the odds of a robbery on a high racial heterogeneity segment are higher from 6pm to midnight.

Ancillary models: Testing interactions between population and business employees

As one final check, it is possible that we should consider simultaneously the effects of population and employee density given that they are each impacted by the daily flows of persons. Thus, we might expect that primarily business areas—that is, many employees but few or no residents—will have fewer robberies when employees are in the area but more later at night when employees are not around. In contrast, an area with high population and employee density would only have more robberies late at night and overnight (given the lack of guardianship at those hours). To test this, we included in a model the interactions of the hourly variables with: 1) population; 2) the particular employee variable; 3) a three-way interaction with population and the employee variable. We tested each of the five employee measures in separate models. We tested the segment measures in five models, and the surrounding area measures in five models.

In general, we found few substantively notable interaction effects. Whereas some effects were statistically significant, plotting them showed very modest effects. The only notable interaction effects were detected for the total employees or retail employees on the segment on weekends. Figure 6 plots the results for the models for total employees and population on the segment on weekends for three levels of population crossed with three levels of total employees. For the most part the lines are parallel, indicating that the effects for population or total employees are largely independent of one another. The most notable difference is that in the late evening—from about 8pm to midnight—there is a large difference in the robbery risk in high employment segments depending on the population density. Thus, the highest line is for high employee and population segments and continues showing increasing robbery risk during these hours, whereas the line for high employee but average population levels off, and the line for high employees and low population actually shows a slight decrease in these hours. A similar pattern was detected for the interaction between population and retail employees. However, no other such effects were detected for the other employee measures.

<<<Figure 6 about here>>>

Conclusion

This study has explored the spatial and temporal pattern of robberies in street segments across the Southern California landscape. An important contribution is that we assessed and found evidence that the relationship between key socio-structural or physical characteristics of the segment and the surrounding area exhibit a temporal pattern in their relationship with robbery risk. Determining these temporal patterns is important as it can provide insight into how these measures are related to crime at different hours of the day, and our innovative approach provides this information without imposing any a priori specific temporal time periods. We have highlighted that although these measures are time-invariant, given the temporal regularity of spatial patterns of persons we would expect these measures to have different meanings at different times of day and days of the week, and therefore result in different relationships with robbery levels. We discuss three key results of temporal patterns that relate to insights of crime pattern theory.

First, one focus of the present study was the temporal pattern between certain crime attractors and robberies, and the results build on previous analyses of these relationships using pre-identified time periods (Haberman & Ratcliffe, 2015). Our approach that utilized a nonlinear parametric function on the robbery level at various times of day was able to determine that for both bars and liquor stores the robbery risk is particularly elevated later in the evening time periods when these facilities are most likely to be patronized. Our flexible temporal approach found that the greatest risk around bars does not appear until after midnight: this highlights that it is not simply the presence of people nearby, but likely the presence of more inebriated people (and therefore more attractive targets) that increases this robbery risk. In the case of liquor stores, the higher robbery risk on weekdays was already present by 8pm, which likely highlights that this is due less to inebriated patrons (given the lack of onsite consumption) but rather due to the increased presence of targets and offenders. Furthermore, these effects were spatially localized to the street segment, emphasizing that these facilities experience robberies because they provide potential targets in the form of patrons, or because the facilities themselves are the robbery target. There may be additional increased robberies one or two segments away from the attractor, although we did not test this here (e.g., Groff & Lockwood, 2014).

Second, we also found that measures capturing the presence of both employees and the customers patronizing locations—specifically, the number of retail employees and the number of restaurant employees—tended to experience the greatest increases in robberies in the afternoons. The presence on the street segment of retail or restaurants resulted in an elevated risk for robberies in the afternoons on weekends. The fact that this temporal pattern was not detected for these segments on weekdays may indicate that it is the greater patronage of these establishments during the daytime on weekends that is driving these results. Furthermore, our approach found this elevated effect on weekends for retail by 10am, whereas restaurants were not observed until noon (likely directly related to lunchtime patterns). This highlights that better measures of temporal patterns of people may further improve these temporal estimates. It was notable that the broader spatial presence of retail and restaurants has a particularly strong temporal effect. The presence of retail and restaurants in broader spatial districts likely impacts the number of patrons, and we found that such locations experienced an elevated robbery risk well into the evening on both weekdays and weekends. This implies that these shopping districts are at elevated risk of robberies even on the adjacent streets that may or may not contain such businesses. The fact that it occurs later in the evening when such locations likely have fewer customers (particularly if retail establishments are closed) implies that such opportunities may occur due to persons on streets appearing as more attractive targets if there are fewer available guardians. The fact that this effect is observed in the general area—and not on the street segments with more establishments themselves—further emphasizes that these may be street robberies upon vulnerable targets. This highlights the importance of considering not just the location of these businesses, but how they impact the walking patterns of persons (Hipp, 2016).

Third, the temporal impact of job subcenters (based on the total number of employees) exhibited strong temporal effects on robbery that notably differed depending on the spatial scale of the measurement. Street segments with more total employees experienced more robbery risk on weekends, but no temporal relationship on weekdays. Given that such locations likely have the most employees present during the day on weekdays, it appears that this temporal pattern is not related to the high presence of workers in the location. Instead, it appears that it is the *lack* of employees at such locations that results in greater robbery risk for the few persons at these locations on weekends. Even more notable was that this effect was swamped by the number of total employees in the surrounding area, which exhibited a *negative* relationship with robberies that was much stronger than the effect at the segment level. Thus, it was notable that a segment in a general employment area—that is, segments surrounded by a high number of total jobs—actually had lower robbery rates during the daytime on all days, even if it had a high number of total employees itself. This is consistent with the idea that the presence of so many workers during normal employment hours provides enough guardianship to reduce robbery levels. Why such locations also had fewer robberies during the day on weekends is less clear, since we would not expect a large number of employees to be working during these hours, and should be explored further in future research. One possibility is that if these are areas with fewer amenities to attract offenders—given that it is primarily an employment subcenter—the lack of targets or offenders on weekends depresses robberies. This would be consistent with the positive micro spatial effect for robberies we detected on weekends in locations not in employment subcenters. These results highlight the importance of accounting for the characteristics of the broader area around a segment.

We acknowledge some limitations to this study. First, our estimation strategy assumed a particular parametric time trend over hours of the day to provide more interpretable results. Although we used a particularly flexible parametric form (a cubic form), this should nonetheless be kept in mind and other functional forms should be tested in future research, including those explicitly based on circular statistics (Kimpton, Corcoran, & Wickes, 2017). A related point is that this parametric form has difficulty capture micro-temporal trends in which there are spikes in crime at particular time points. Although such spikes are of interest, testing them requires much data given the sparseness of crime, and/or strong theory about specific time points to test. Third, our covariates were not measured temporally; it would be preferable to know how many people, and what types of people, are in an area at a point in time, but we lacked such data. Recent scholarship has attempted to measure the ambient population at locations during different hours of the day (Hipp, et al., 2017; Malleson & Andresen, 2016), and while these approaches are promising, they nonetheless rely on sources of data whose validity is uncertain. We also lacked information on the specifics of the robbery event, and thus could not distinguish between those with or without a gun, etc.

This study has highlighted that there are important temporal, as well as spatial, patterns to crime. The results reinforce prior research finding that crime attractors inflate crime at certain times of day (Haberman & Ratcliffe, 2015). The findings also highlight that locations that likely operate as crime generators, such as employment or retail districts, only have elevated crime levels during certain time periods. We believe that exploring temporal differences in these relationships is a fruitful direction for future research that will better unravel the processes that are occurring in crime and place studies. Our strategy that parametrically estimated these relationships over the hours of the day—rather than making a priori assumptions about key time periods—is a useful one as criminologists continue exploring these temporal crime patterns.

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Tables and Figures

Table 1. Summary statistics of variables used in analyses

	Street segment		Spatially lagged measures (0.5 miles)	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Robbery (0/1)	0.004	0.066		
Proportion of vacant land use	0.093	0.239	6.711	13.833
Concentrated disadvantage	-1.725	9.210	-0.735	7.920
Residential stability	-0.085	0.837	-0.044	0.791
Racial/ethnic heterogeneity	0.417	0.186	0.484	0.152
Percent Black	6.639	13.337	5.442	9.827
Percent Latino	35.310	29.118	38.366	27.409
Percent Asian	11.294	13.190	11.354	10.838
Percent vacant units	6.904	10.070	5.779	4.924
Percent aged 16 to 29	19.909	9.256	21.496	6.820
Population (logged)	4.646	1.482	0.450	1.331
Total employees	1.067	1.332	8.471	1.741
Retail employees	0.194	0.625	5.975	1.843
Bar employees	0.007	0.120	1.481	1.764
Liquor employees	0.006	0.099	1.485	1.498
Restaurant employees	0.070	0.458	4.664	2.436
Weekend (0/1)	0.321	0.467		
Weekend hours	1.929	3.453		
Weekday hours	3.571	3.711		

N = 18,312,453 2-hour time periods

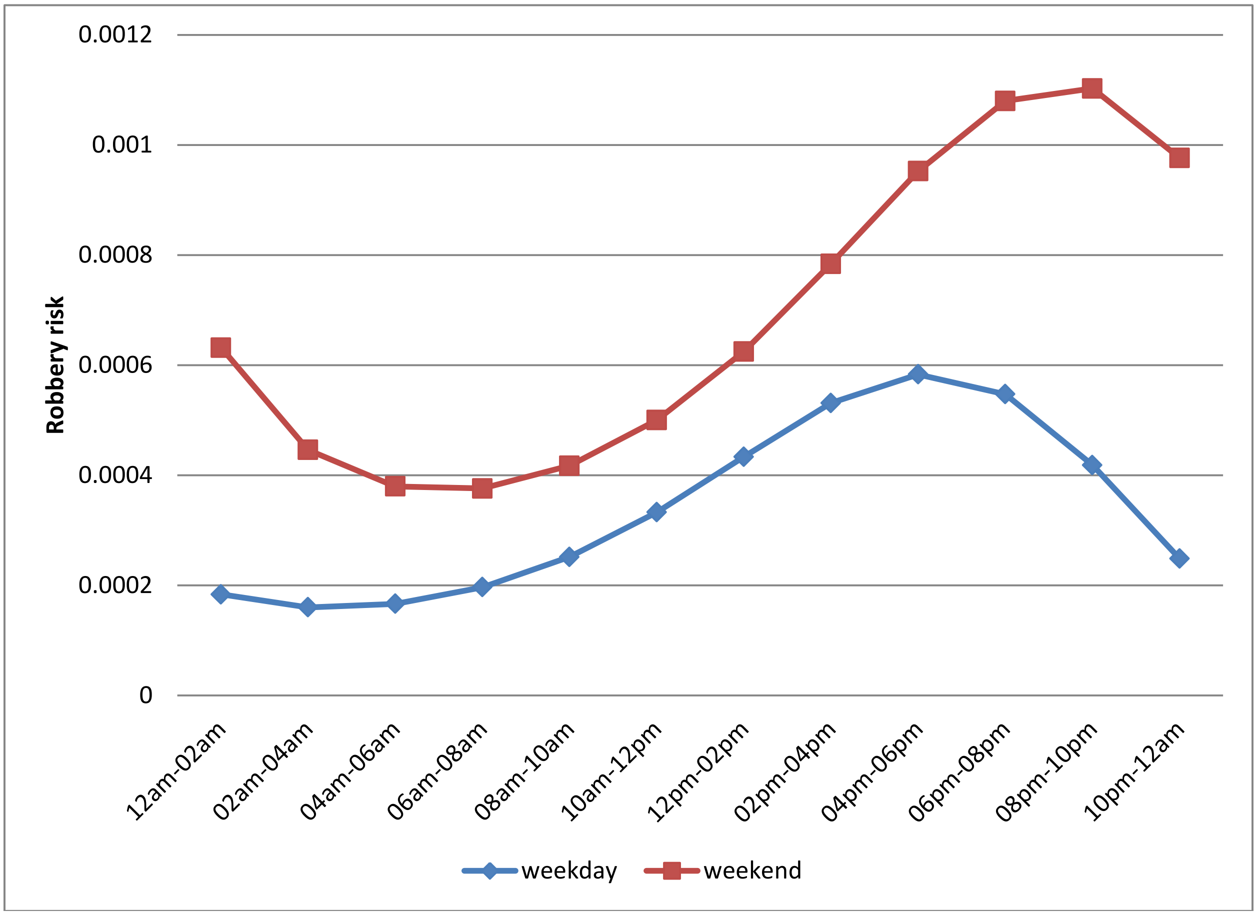
Table 2. Summary of results for interaction variables capturing temporal effects

	Segment			Nearby		
	Dir.	Weekday	Weekend	Dir.	Weekday	Weekend
Population (logged)	pos		6pm-4am			
Proportion of vacant land use						
Concentrated disadvantage						
Residential stability	neg	8pm-4am		pos	8am-6pm	8am-6pm
Racial/ethnic heterogeneity	pos	6pm-mid				
Percent Black	pos	6am-4pm	8am-4pm	pos	6am-4pm	8am-4pm
Percent Latino						
Percent Asian						
Percent vacant units	neg		8pm-mid			
Percent aged 16 to 29	pos		10pm-4am			
Total employees	pos		10am-6pm	neg	6am-6pm	10am-6pm
Retail employees	pos		10am-6pm	pos	10pm-4am	10pm-6am
Bar employees	pos	mid-6am	mid-6am	pos	10pm-4am	10pm-6am
Liquor employees	pos	8pm-4am				
Restaurant employees	pos		noon-6pm	pos	8pm-4am	10pm-6am

Note: Dir.: direction of temporal effect (pos= positive, neg=negative). Time ranges show the period of the strongest temporal effect

Temporal Dimensions of Robbery

Figure 1. Predicted robbery probability by 2-hour period, by weekdays and weekends



Temporal Dimensions of Robbery

Figure 2a. Robbery risk based on total employees in segment (low, medium, high)– weekends

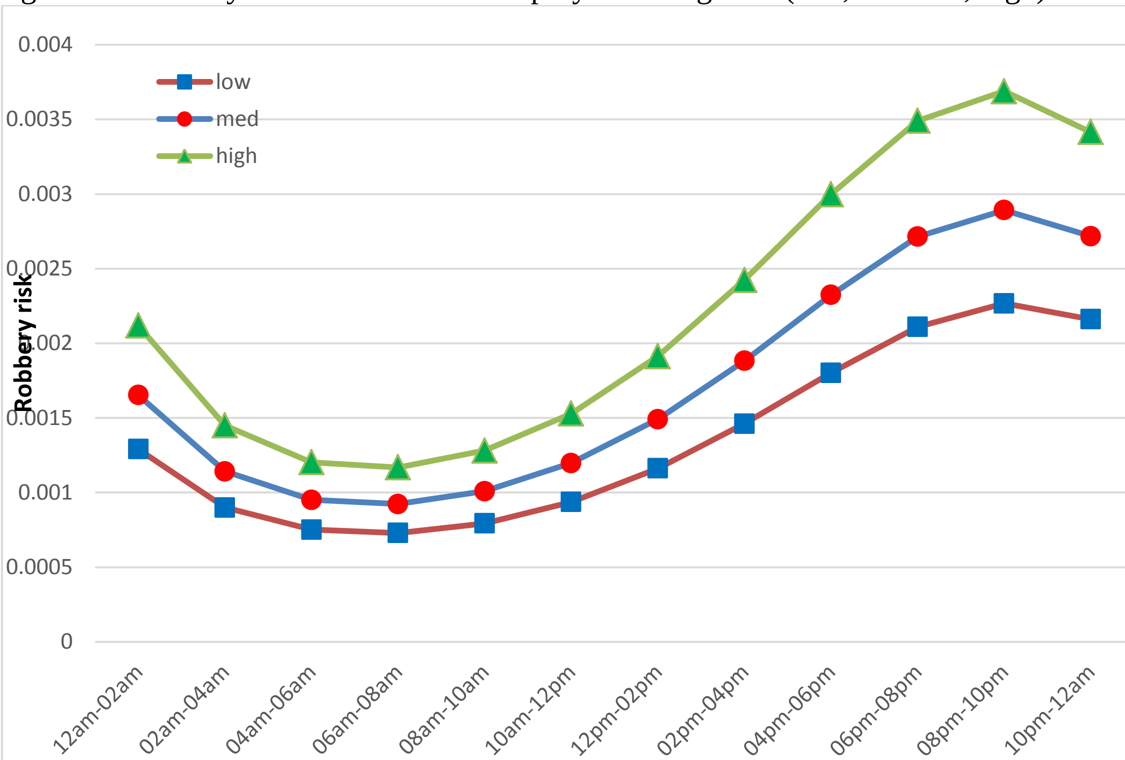
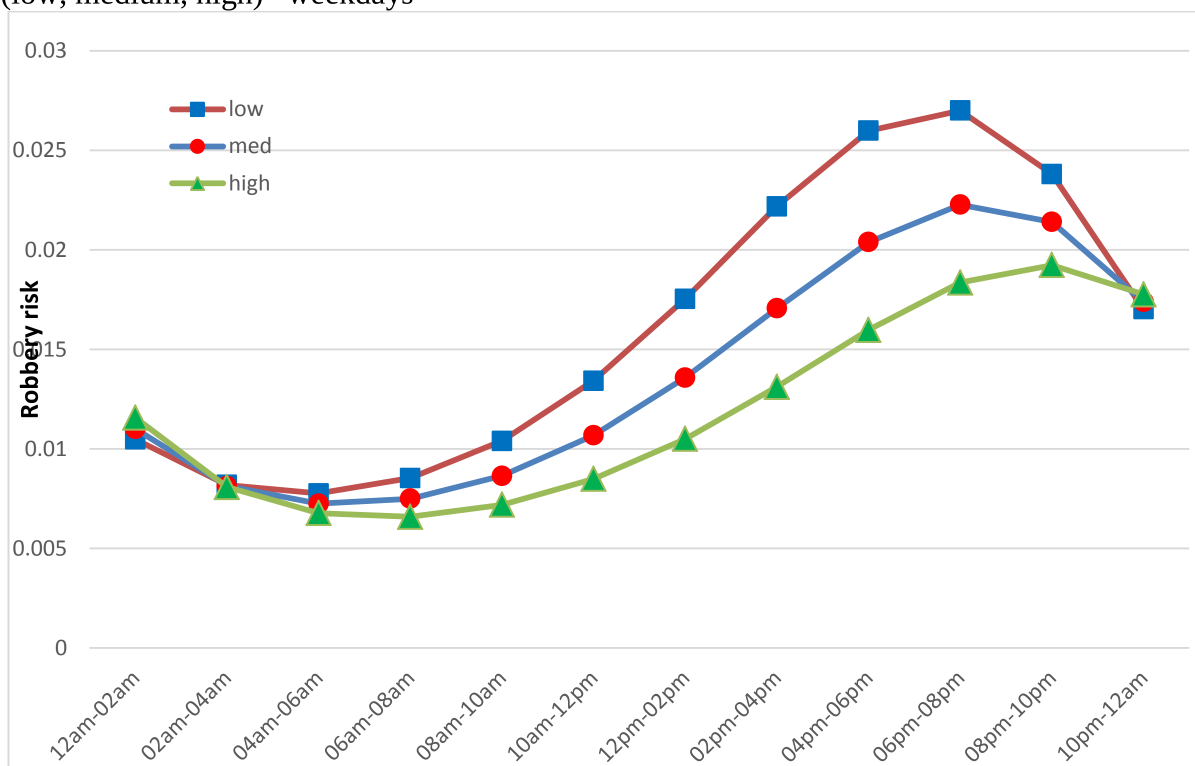


Figure 2b. Robbery risk based on total employees in surrounding ½ mile inverse distance decay (low, medium, high)– weekdays



Temporal Dimensions of Robbery

Figure 3a. Robbery risk based on retail employees in surrounding ½ mile inverse distance decay (low, medium, high)- weekdays

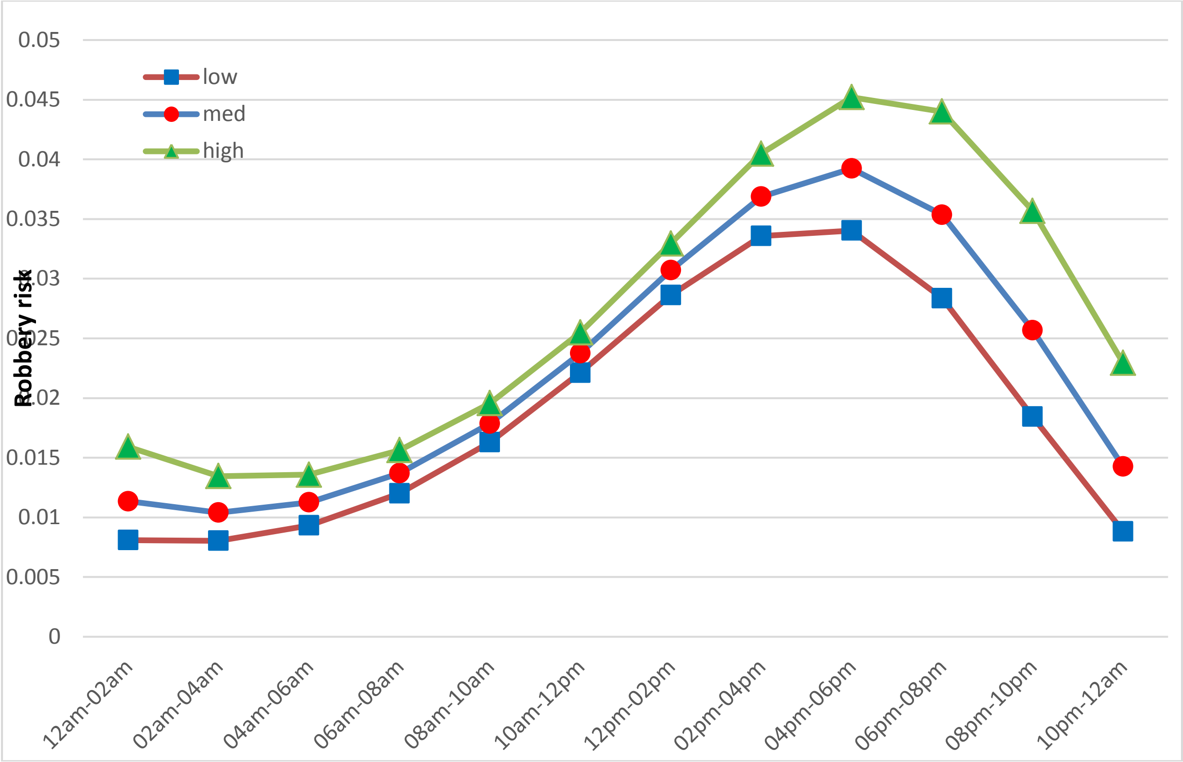
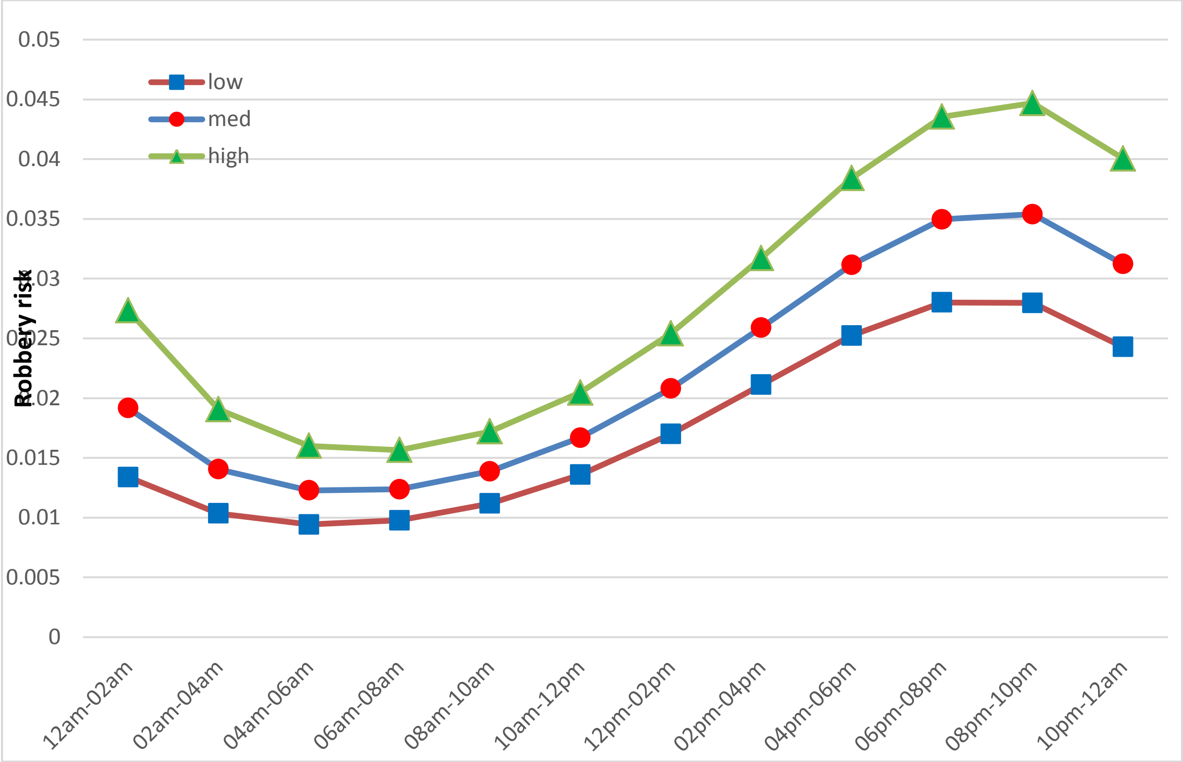
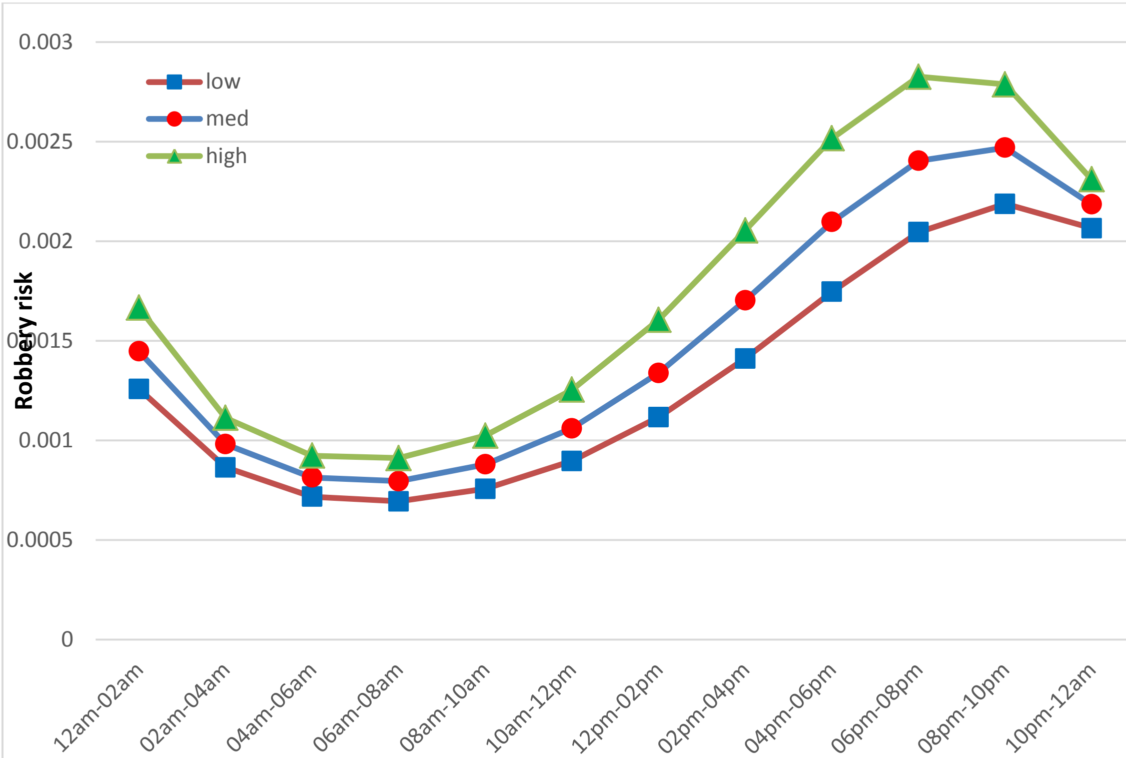


Figure 3b. Robbery risk based on retail employees in surrounding ½ mile inverse distance decay (low, medium, high)– weekends



Temporal Dimensions of Robbery

Figure 4. Robbery risk based on restaurant employees in segment (low, medium, high)-weekends



Temporal Dimensions of Robbery

Figure 5. Robbery risk based on population in segment (low, medium, high)– weekends

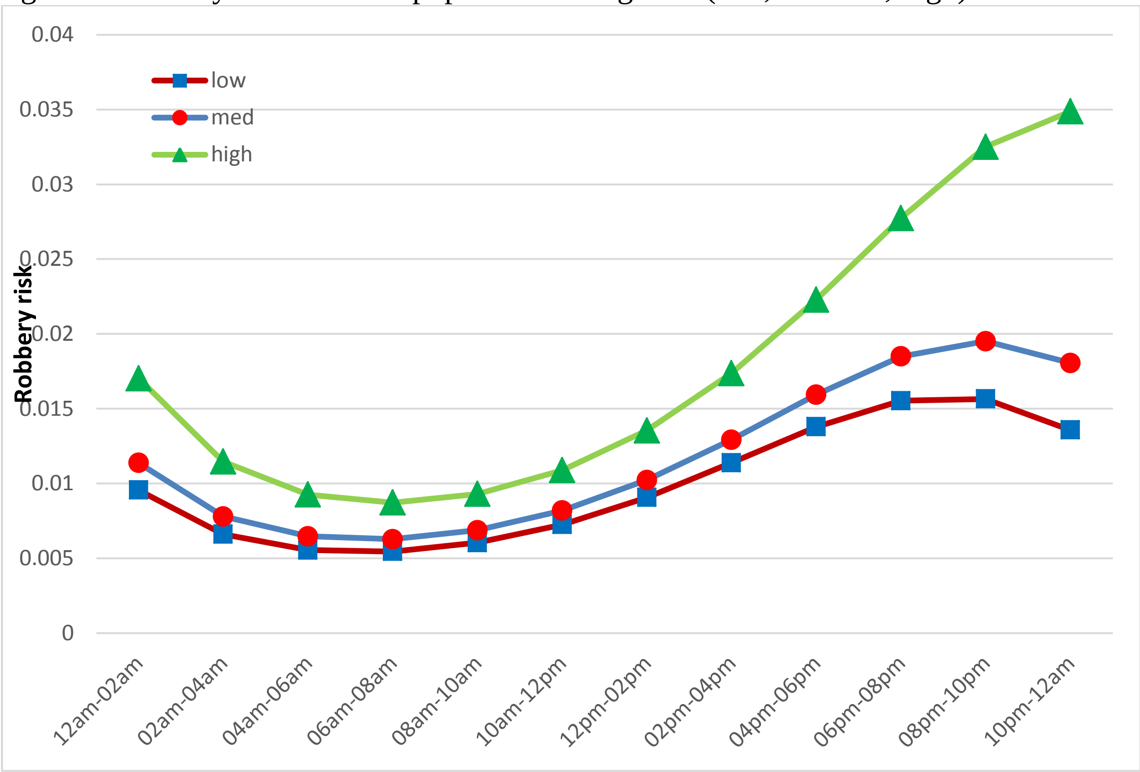
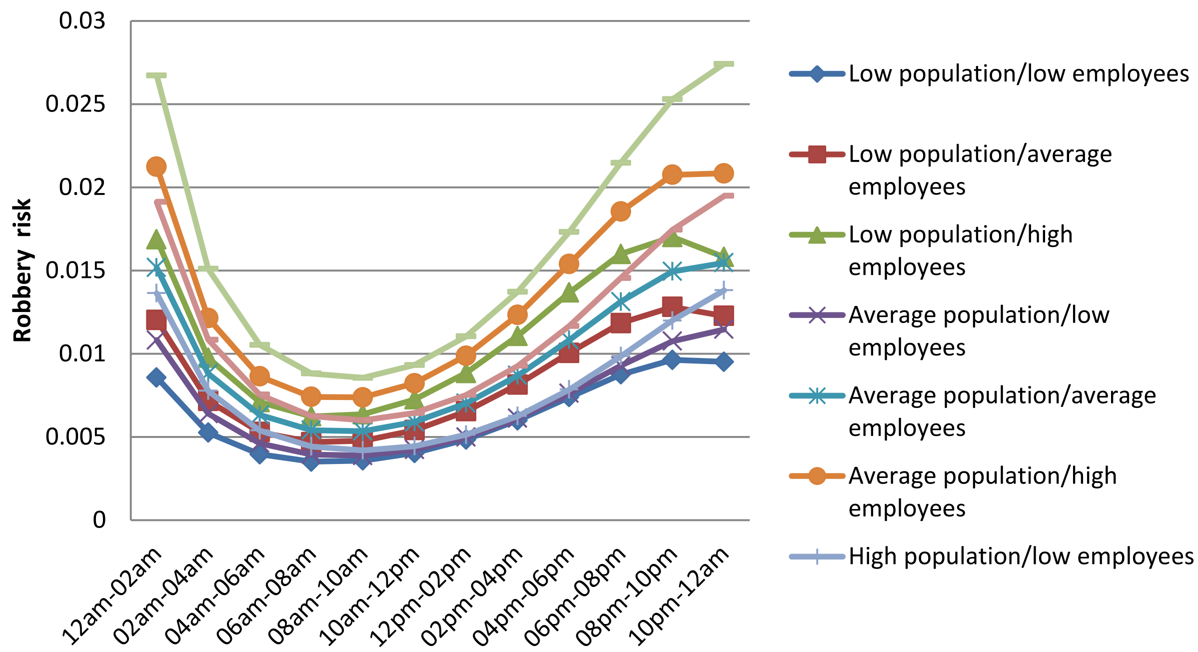


Figure 6. Interaction of population and total employees in segment on weekends



Appendix

Table A1. Main effects logistic regression model with robberies in 2-hour period as outcome variable

	Street segment			Surrounding 1/4 mile	
Socio-demographic variables					
Percent vacant land use	-0.349			-1.253	
	-(1.82)			-(1.95)	
Concentrated disadvantage	0.015	**		0.044	**
	(13.57)			(4.17)	
Residential stability	-0.233	**		0.184	**
	-(26.41)			(6.05)	
Racial/ethnic heterogeneity	-0.307	**		0.254	
	-(4.95)			(1.36)	
Percent black	0.002	*		0.021	**
	(2.45)			(4.84)	
Percent Latino	0.002	*		0.005	
	(2.54)			(1.57)	
Percent Asian	0.002	*		-0.006	
	(2.08)			-(1.26)	
Percent vacant units	0.002			0.032	**
	(1.69)			(6.90)	
Percent aged 16 to 29	-0.005	**		0.009	**
	-(12.71)			(4.70)	
Population (logged)	0.133	**		0.666	**
	(16.55)			(11.38)	

Employees variables					
Total employees (logged)	0.275	**		-0.088	**
	(15.63)			-(3.58)	
Retail employees (logged)	0.258	**		0.106	**
	(35.78)			(4.36)	
Bar employees (logged)	0.117	**		-0.005	
	(9.30)			-(0.64)	
Liquor employees (logged)	0.240	**		0.004	
	(11.64)			(0.26)	
Restaurant employees (logged)	0.159	**		0.068	**
	(15.83)			(9.25)	
Day and hour variables					
Weekend	0.756	**			
	(15.49)				
Hour on weekend	-0.696	**			
	-(18.92)				
Hour on weekday	-0.487	**			
	-(16.24)				
Hour on weekend squared	0.130	**			
	(17.85)				
Hour on weekday squared	0.135	**			
	(24.14)				
Hour on weekend cubed	-0.006	**			
	-(16.44)				
Hour on weekday cubed	-0.008	**			
	-(26.46)				
Intercept	-7.550	**			
	-(47.96)				
Pseudo r-square	0.174				
*Note: ** P < .01; * p < .05. T-values in parentheses.*					

Table A2. Coefficient estimates for interactions between hour of day and variable of interest

Models for segments	**Interaction variables**														
	Population	**Vacant L.U.**	**Con. Dis.**	**Res. Stab.**	**R/E hetero**	**% Black**	**% Latino**	**% Asian**	**% Occupied**	**% aged 16-29**	**Total emps**	**Retail emps**	**Bar emps**	**Liq. emps**	**Rest. emps**
Interaction terms															
Interaction weekday hours	-0.0202	0.1391	0.0065	0.0342	-0.0484	0.0037 **	0.0002	-0.0033	-0.0007	-0.0033	-0.0024	-0.0005	-0.1086 **	0.0786 *	0.0030
	-1.6863	0.5798	1.5648	1.5332	-0.4843	5.3879	0.1031	-1.2007	-0.7440	-1.8156	-0.2231	-0.0376	-4.1625	2.1345	0.2555
Interaction weekend hours	0.0045	0.1349	0.0046	0.0336	-0.1329	0.0019 **	0.0014	-0.0009	0.0018 *	0.0012	-0.0211 **	-0.0322 **	-0.1411 **	0.0337	-0.0539 **
	0.4858	0.8923	1.1314	1.3283	-1.2198	2.6439	1.6033	-0.3332	2.2235	0.9589	-2.9054	-3.6460	-3.3211	0.4186	-5.0122
Interaction weekday hours (sq)	0.0012	-0.0601	-0.0006	0.0028	-0.0152	-0.0003 *	0.0002	0.0002	0.0002	0.0005	0.0003	0.0019	0.0118	-0.0230 **	-0.0001
	0.4659	-1.1178	-0.9325	0.8731	-1.3072	-2.3077	0.7582	0.7144	1.4350	1.6260	0.1757	0.7554	1.5007	-3.1639	-0.0597
Interaction weekend hours (sq)	-0.0055 *	-0.0540	-0.0003	-0.0002	0.0078	0.0001	-0.0002	0.0000	-0.0006 **	-0.0006 *	0.0062 **	0.0122 **	0.0225	-0.0020	0.0161 **
	-2.5157	-1.5311	-0.3985	0.0462	0.3771	0.6611	-1.6293	-0.3292	-2.6456	-2.3405	4.7445	6.7472	1.3048	-0.1362	7.4978
Interaction weekday hours (cu)	0.0001	0.0043	0.0000	-0.0005 **	0.0020 *	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0002	-0.0004	0.0016 **	0.0000
	0.5998	1.4724	0.1020	-3.3176	2.2108	0.1324	-1.5549	0.4461	-1.3448	-1.2691	-0.2775	-1.4105	-0.7659	4.2982	-0.3268
Interaction weekend hours (cu)	0.0005 **	0.0037	0.0000	-0.0002	0.0003	0.0000 **	0.0000	0.0000	0.0000 **	0.0000 **	-0.0004 **	-0.0009 **	-0.0011	0.0000	-0.0011 **
	3.7824	1.7231	-0.2722	-1.0451	0.4365	-3.2194	1.6540	0.3818	2.7766	2.9863	-4.7349	-7.9475	-0.9194	0.0375	-7.8400

Models for nearby area	**Interaction variables**														
	Population	**Vacant L.U.**	**Con. Dis.**	**Res. Stab.**	**R/E hetero**	**% Black**	**% Latino**	**% Asian**	**% Occupied**	**% aged 16-29**	**Total emps**	**Retail emps**	**Bar emps**	**Liq. emps**	**Rest. emps**
Interaction terms															
Interaction weekday hours	-0.0861	0.1361	0.0090	0.0705 **	-0.1182	0.0050 **	0.0005	-0.0056	-0.0056	-0.0042	-0.0508 **	-0.0472 *	-0.0450 **	-0.0222	-0.0336
	-1.3402	0.2440	1.3190	4.2280	-0.7178	3.9417	0.2788	-1.0593	-1.4065	-1.2328	-3.0852	-2.3116	-2.8807	-1.5362	-1.9387
Interaction weekend hours	-0.0241	-0.4980	0.0091	0.0697 **	-0.2185	0.0032 **	0.0013	-0.0018	-0.0049	0.0001	-0.0200	-0.0381 **	-0.0096	-0.0018	-0.0334 *
	-0.3853	-0.4282	1.6076	3.8203	-1.8898	2.5796	0.8575	-0.3553	-1.4208	0.0404	-1.4659	-3.7275	-0.7059	-0.1063	-2.5027
Interaction weekday hours (sq)	0.0059	-0.0274	-0.0006	0.0039	-0.0133	-0.0004	0.0002	0.0005	0.0002	0.0007	0.0004	0.0016	0.0020	0.0010	-0.0002
	0.4137	-0.2017	-0.5210	1.5446	-0.8272	-1.6885	0.6132	0.7633	0.2549	0.9749	0.0985	0.5231	1.0537	0.3975	-0.1756
Interaction weekend hours (sq)	-0.0062	0.0396	-0.0008	-0.0005	0.0251	0.0000	-0.0001	-0.0001	0.0005	-0.0006	-0.0039	0.0039 *	-0.0048 **	-0.0024	0.0032 *
	-0.4351	0.1455	-1.0870	-0.1318	1.3448	-0.1243	-0.5248	-0.5793	0.4196	-0.8485	-1.6987	2.2407	-2.7718	-1.2803	2.5597
Interaction weekday hours (cu)	0.0002	0.0002	0.0000	-0.0009 **	0.0023	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003 *	0.0002	0.0001 **	0.0001	0.0003 **
	0.2108	0.0339	-0.4756	-6.1923	1.7367	0.1184	-1.4875	0.1451	0.2643	-0.8752	2.5401	1.7108	2.6893	0.4936	3.3065
Interaction weekend hours (cu)	0.0008	0.0006	0.0000	-0.0004 *	-0.0007	0.0000 *	0.0000	0.0000	0.0000	0.0000	0.0004 **	-0.0001	0.0005 **	0.0002	-0.0001
	0.9987	0.0528	0.2299	-2.2957	-0.6666	-2.3146	0.3297	0.5877	-0.3300	1.4509	2.6046	-0.6344	5.3447	1.8539	-0.6925

*** p < .01(two-tail test), * p < .05 (two-tail test). T-values below the coefficients. Each column represents estimates from a distinct model (including all control variables shown in Table A1). N = 13,578,932.*