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Micro-Scale, Meso-Scale, Macro-Scale, and Temporal Scale: Comparing the Relative Importance for Robbery Risk in New York City

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Micro-scale, meso-scale, macro-scale, and temporal scale: Comparing the relative importance for robbery risk in New York City

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Micro-scale, meso-scale, macro-scale, and temporal scale:

Comparing the relative importance for robbery risk in New York City

Abstract

We compare the relative importance of four dimensions for explaining the micro location of robberies: 1) the micro spatial scale of street segments; 2) the meso spatial scale surrounding the street segment; 3) the temporal pattern, and 4) the macro-scale of the surrounding 2.5 miles. This study uses crime, business, and land use data from New York City and aggregates it to street segments and hours of the day. Although the measures capturing the micro-scale of the street segment explained the largest amount of unique variance, the measures capturing temporal scale across hours of the day (and weekdays) explained the next largest amount of unique variance. The measures of the characteristics in the 2.5 miles macro scale explained the next largest amount of unique variance, and combined with the measures at the meso-scale explained nearly as much of the variance as the street segment measures.

Keywords: street segments; crime; spatial scale; temporal scale; population density.

Bio

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Micro-scale, meso-scale, macro-scale, and temporal scale: Comparing the relative importance for robbery risk in New York City

A burgeoning body of literature has focused on the tendency for crime to cluster at particularly micro locations (Hipp and Kubrin 2017; Weisburd 2015; Haberman, Sorg, and Ratcliffe 2017). As a consequence, recent studies have attempted to explain why crime is more likely to occur at certain small geographic units (e.g., street segments) than on others (Weisburd, Groff, and Yang 2012; Schnell, Braga, and Piza 2017; Bernasco and Block 2011). These studies explore whether characteristics of the local street segment, or nearby segments, impact the level of crime on the segment itself, and typically employ routine activities theory and its geographic corollary crime pattern theory, and have contributed to a growing body of evidence regarding this question. A challenge with routine activities and crime pattern theory is that they have an explicit temporal component to them that requires temporal precision in measuring the presence of offenders and targets in the same location at the same time (Felson and Boba 2010). This temporal precision is rarely accounted for in studies. Furthermore, the fact that most of such studies typically focus on only a single city with a particular macro-environment raises the question of generalizability of such findings across different macro scales.

These considerations imply four particular dimensions that may vary across contexts, and that we focus on here: 1) the micro scale of street segments; 2) the meso scale of characteristics of nearby segments; 3) the temporal pattern of robbery; 4) the macro-scale of the broader environment. First, despite the increasing focus on the clustering of crime at micro locations and the insights it has provided, recent work demonstrates that there is a risk of a ‘too narrow’ lens that ignores the characteristics of the nearby environment when studying spatial crime patterns (Boessen and Hipp 2015; Groff 2014; Bernasco and Block 2011; Ratcliffe 2012; Kim and Hipp 2019). Although crime attractors and generators bring offenders and targets to specific street segments, the travel paths of persons imply that nearby streets may also be at elevated risk of crime incidents, particularly for robberies (Reid et al. 2013). Thus, there is a need to take into account the characteristics of nearby segments when studying why some segments have more crime than others.

Second, a key insight of routine activities theory is that crime is more likely to occur when there is a spatial *and* temporal confluence of offenders and targets in the absence of guardians (Felson and Boba 2010; Cohen and Felson 1979). Thus, although this theory contains both a spatial and a temporal component, and existing research often takes great care in measuring it spatially, only recently have studies have begun to test this theory with an explicit temporal component (Haberman and Ratcliffe 2015; Boessen 2014; Hipp 2016; Hipp and Kim 2019; Hipp et al. 2019). Nonetheless, an implication is that to understand when and where crime will occur it is necessary to measure the ambient population at a location over various hours of the day. This implies a need to also measure the daytime population, which is largely determined by the presence of employment locations, as well as commercial districts that draw in customers.

Third, various dimensions at the macro scale are important for determining the micro location of crime, including economic inequality and broader residential density patterns (Smith, Frazee, and Davison 2000; Boessen and Hipp 2015; Boivin and Felson 2018). Thus, the well-known spatial patterns exhibited by offenders (Rossmo 2000) whose median distance traveled to crime events often exceeds one mile, combined with the opportunities at micro locations, would likely lead to a more complicated spatial pattern (Hipp 2016). Indeed, recent work comparing results across four very different spatially organized cities found evidence that this has consequences for the determinants of robbery at micro locations (Hipp, Wo, and Kim 2017). And scholarship focused on egohoods in a single city found a robust effect in which the level of economic inequality in a surrounding 2.5 mile radius impacted block levels of crime (Hipp and Kubrin 2017). Nonetheless, scholarship has generally paid limited attention to this broader macro-scale.

In this study, we explicitly compare the relative contribution of these four dimensions for understanding when and where robberies occur: the local spatial scale of street segments and the nearby area; the temporal pattern, and the macro-scale of the broader area (i.e. the surrounding 2.5 miles). We use New York City as our study site to explore these research questions given that it affords us a wide variety of population and workplace density, allowing for a wide range of comparisons. The high density of New York City provides a good environment for studying the micro scale at which characteristics of nearby segments impact the level of crime on a segment. Given the vibrancy of New York City, it is also a good location to study temporal patterns. Another advantage of the New York City area is that despite the fact it is a single city, the considerable variability in density *across* the five boroughs (Bronx, Brooklyn, Manhattan, Queens, Staten Island) allows us to gain a better understanding of how this density at the macro scale is related to the location of crime. This is important given that these effects may not simply scale in a linear fashion over different densities, but may instead exhibit nonlinear effects. One reason that so little research has focused on New York City may be because it is so different from other cities given its very high population and business density (Feng et al. 2018; Weisburd, Tellep, and Lawton 2014). However, given the recent push for higher density in cities based on the insights of the new urbanist perspective (Congress for the New Urbanism 2001; Talen 2002) as well as the push for greater regional sustainability based on shorter commuting patterns (Cervero and Duncan 2006), we argue that key insights can be obtained from studying New York City.

Literature Review

The micro context of crime and spatial patterns

A body of research has focused on the micro context of crime. This research typically builds on the environmental crime literature (Brantingham and Brantingham 2008; Brantingham and Brantingham 1984; Brantingham and Brantingham 1995, 1993) and how it relates to the routine activity perspective's focus on the presence of offenders, targets, and guardians. An important implication of this perspective is the need to measure the presence of people at locations throughout the hours of the day. Nonetheless, a large focus of this literature is how certain types of establishments—such as liquor stores, bars, or fringe banks (Kubrin and Hipp 2016; Pridemore and Grubesic 2013)—provide a high number of crime opportunities and hence have more crime (Bernasco and Block 2011; Haberman and Ratcliffe 2015; Steenbeek et al. 2012; Browning et al. 2010; Stucky and Ottensmann 2009). These locations providing increased crime opportunities are indeed sometimes associated with increased levels of crime. It should be noted that these studies implicitly focus almost entirely on the spatial distribution of crime targets and therefore typically do not account for the ambient population, or the location and spatial patterns of offenders.

Nearby environment for impacting spatial patterns of crime

Although the crime and place research has highlighted that exploring the characteristics of micro-locations can provide insights on the location of crime events, a risk is focusing only on the characteristics of the micro location to the exclusion of the surrounding area. The problem with this strategy is that the nearby area likely matters as well; indeed, Bernasco and Block (2011) pointed out that the use of ever smaller geographic units almost certainly implies that the effect of the "nearby" area will be even more pronounced. Studies have recognized the importance of taking into consideration nearby areas in addition to the focal street segment when studying drinking places and crime. For example, Groff (2014) included measures of drinking places within the segment as well as a buffer surrounding it and found robust effects. Another study found that nearby criminogenic facilities within ¼ mile were related to levels of crime (Groff and Lockwood 2014). Ratcliffe (2012) found that the spatial decay of crime around bars exhibited a sharp decay, and also studied the spatial decay of crime attractors more generally (Ratcliffe 2011, 2012). Boessen and Hipp (2015) in a study of blocks across several cities found that the characteristics of the surrounding block group, as well as the broader area around the block group, were robustly associated with crime levels in blocks. Indeed, given the spatial patterns of offenders, whose median distance traveled to crime events typically exceeds one mile (Rossmo 2000) we would expect that crime events would not just occur on the segment itself. A nascent body of work studies how potential paths taken by offenders can influence the location of crime (Reid et al. 2013), which implies a spatial patterning to where crimes occur based on where people are located at times of the day.

Indeed, for some crime generators, offenders may not wish to offend precisely at the specific location. This is because a particular location may not only have a large number of potential targets, but also a large number of other people who can serve as guardians (Felson and

Boba 2010). For this reason, it may be more attractive for offenders to target potential victims when they walk a block or two away from the location (with fewer potential guardians nearby). For example, research has shown that whereas crime is more likely to occur on blocks with fringe banks, it is also more likely to occur one or two blocks away as well (Kubrin and Hipp 2016). Research has similarly detected a tight spatial pattern for other crime generators (Bernasco and Block 2011; Groff and McCord 2011; Groff and Lockwood 2014).

Finally, the social disorganization perspective posits that various socio-structural characteristics of neighborhoods are important for determining an area's ability to address crime either through informal social control or petitioning for additional community resources (Sampson and Groves 1989; Bursik 1988). There are debates about the proper spatial scale for measuring such "neighborhood" characteristics, with some positing that the local street segment may operate as a neighborhood (Taylor 1997), whereas other research has highlighted that a broader area may be important to consider (Boessen and Hipp 2015; Hipp 2007). We assess this here by constructing measures at both spatial scales.

Temporal considerations for crime incidents

Beyond the locations of crime attractors, and where offenders might live, an important characteristic for understanding the micro location of crime is accounting for the spatial and temporal pattern of where persons go, as they may be potential targets. This is necessary for better capturing the confluence of offenders and targets (Hipp 2016). Thus, one body of research has attempted to measure the ambient population and how it is related to local crime. That is, the presence of persons at various hours of the day may be related to increased levels of crime at these specific times. This body of research focuses on the ambient population that is present at locations throughout the day, and the consequences for crime (Andresen 2011; Malleson and

Andresen 2015; Malleson and Andresen 2016). Some of these studies have used the LandScan dataset, which provides estimates of the potential ambient population averaged across hours of the day based on information about the residential population and the locations of businesses. Whereas many of these studies have attempted to measure the ambient population in an effort to obtain a more appropriate denominator when computing crime rates, one study used Twitter information as a proxy of the ambient population typically at a location during *specific hours*, and demonstrated a positive relationship with crime during those hours (Hipp et al. 2019). Another recent study used information on the number of employees at various micro locations as a proxy for the potential ambient population, and found it had a positive relationship with robberies that varied across hours of the day (Hipp and Kim 2019). We follow this latter approach in the current study.

An important component for measuring the ambient population is the residential population of a location (Hipp and Roussell 2013; Boivin and Felson 2018; Roncek 1981; Roncek and Maier 1991). However, although the residential population may indeed best capture the population at a location overnight, during the daytime many of those people may leave the location to commute to work. Instead, measures of the total employees in a location are important for capturing the daytime population in a location. Furthermore, commercial establishments typically not only have employees, but also draw in customers. For this reason, scholars have used the number of retail employees at a location as a proxy for the number of customers coming to a location during the daytime or evening (Wo 2016; Hipp 2010; Boessen and Hipp 2015; Hipp 2007; Bowes 2007). Thus, retail establishments can attract people during the daytime or evening, and restaurants and other food providing locations can attract patrons during mealtimes in the day or later into the evening. By accounting for measures of various types of employees, or the residential population in a location, scholars have attempted to create estimates of the ambient population in a location throughout the day.

In all of these considerations of ambient population, it is important to study the spatial *and* temporal convergence of people in space for understanding the time and location of crime events. For example, the presence of many targets, but few offenders, will not lead to higher levels of crime. Thus, characteristics of the environment may have different relationships with the level of crime that occurs during particular time periods. For example, the residential population of a location provides a relatively accurate count of the population overnight, but can be less informative during the daytime when many residents are off at their workplaces or engaging in errands. Likewise, a retail district may have a large number of shoppers during the day or early in the evening, but may be relatively abandoned later at night. Thus, these characteristics may have different relationships with crime levels as measured at different times of day (Hipp and Kim 2019).

Some research has tested these possible differences. One study explored this question and focused primarily on measures of crime attractors in assessing whether their relationship with crime incidents differed during certain periods of the day (Haberman and Ratcliffe 2015). Another recent study in Southern California measured whether retail and other similar businesses attract persons during particular hours of the day, and therefore result in increased robbery rates during those specific hours (Hipp and Kim 2019). Ratcliffe (2006) proposed a theory in which temporal constraints upon daily routine activities are major determinants of spatio-temporal patterns of crime: in this model, the temporal need of offenders to return to their home location at the end of the day will result in a spatial pattern in which crime events occur closer to their homes. The implication is that researchers should incorporate multidimensional measures represented by location and time. Other research has attempted to account for the ambient population during all hours of the day by taking into account the number of people who leave a block to attend school or work (Boessen 2014). The findings from these studies suggest that this is a fruitful avenue for further research. New York City is a particularly interesting study area in this regard given that the Manhattan borough has activity over a large portion of the 24 hour day, whereas the other boroughs have temporal activity more similar to most cities in the U.S.

Broader environment for impacting spatial patterns of crime

Both the crime and place research as well as the neighborhoods and crime research has typically focused on smaller geographic units, and paid less attention to whether the relationship between various micro- or meso-level measures and crime holds across different macro environments. Nonetheless, this assumption is worth exploring more in depth. For example, one study explored whether crime generators have different relationships with crime levels across the boroughs of New York City (Feng et al. 2018). Additionally, some recent work has employed a sample of neighborhoods across about 90 cities and assessed whether certain features of the macro city-level environment have independent effects on neighborhood crime beyond meso-level measures (Lyons, Vélez, and Santoro 2013; Velez, Lyons, and Santoro 2015; Peterson and Krivo 2010). This work has found evidence that the level of racial segregation in a city can impact neighborhood-level crime (Peterson and Krivo 2010), and that city-level inequality impacts neighborhood crime levels, above and beyond neighborhood-level characteristics (Chamberlain and Hipp 2015). Other studies have found that various characteristics of a city's political context impact neighborhood-level crime (Lyons, Vélez, and Santoro 2013; Velez, Lyons, and Santoro 2015).

The importance of how meso-level measures vary across macro units was extended by studying how the relationship between measures at the micro-level of blocks were related to crime across four cities with very different population structures (Hipp, Wo, and Kim 2017). This study followed the insights of Hipp and Roussell (2013) and selected four cities that varied along the two dimensions of population in the *micro-environment* (i.e., population density at the local scale) and population in the *macro-environment* (the population of some larger area). Hipp and colleagues (2017) demonstrated that there were key differences across these four very different cities in how various micro-level measures were related to the spatial distribution of crime. The theoretical insight of this study focusing on four specific cities was that the possible locations of offenders can impact the spatial location of crime (Hipp 2016), and that this broader scale can capture this potentiality. Nonetheless, studies rarely account for the possible locations of offenders when exploring the micro location of crime despite the body of research showing that offenders tend to commit crimes with a spatial decay from where they live (Rossmo 2000; Bernasco 2010; Lammers et al. 2015; Bernasco, Ruiter, and Block 2017). An implication is that determining where offenders live could help in understanding the spatial location of crime (Hipp 2016).

Yet another approach combines both macro-level theories as well as insights about the potential movement of offenders. In this strategy, Hipp and Kubrin (2017) accounted for how the broader spatial scale can impact crime not by comparing models across cities, but instead by accounting for the characteristics of a 2.5 mile buffer around each egohood in the single city of Los Angeles. In their approach, they built on ideas from research studying neighborhoods nested in cities that typically relies on macro-level theories to posit city-level characteristics that impact neighborhood-level crime. This study specifically focused on how changes in the level of income inequality and racial heterogeneity in this broader area can impact changes in the level of crime in egohoods over the decade, and found robust evidence that these characteristics of the broader scale impact crime rates, even when controlling for the standard neighborhood measures. We build on this approach here in focusing on how this larger macro environment may impact the level of crime on micro-geographic units, even within a single city. By directly measuring the macro context, rather than simply estimating separate models across the boroughs of New York (Feng et al. 2018), we argue that our approach has the potential to provide key insights. We also directly assess the amount of unique variance explained by these macro measures compared to the variance explained by the meso level measures as a way to assess the relative importance of this macro scale.

Data and methods

Data

We use data capturing our measures in the year 2010. The crime data come from the New York City Police Department (NYPD).[1] NYPD classified the reported incidents to identify all the crimes that may have occurred in the five boroughs of New York City: Bronx, Brooklyn, Manhattan, Queens, and Staten Island. Robbery events (both commercial and individual) were classified using the New York State Penal Law categories (same as the UCR classification). NYPD provided incident crime data with geographic information including longitude-latitude points, and we attached these to the nearest street segment or intersection. In our crime data, the characteristics of robberies at intersections are not different from those at street segments, therefore dropping them is not appropriate. Thus, about 13 percent of events were at intersections, and we evenly randomly assigned them to one of the contiguous street segments

[1] https://opendata.cityofnewyork.us/

(Hipp and Kim 2019). Note that a different approach sometimes adopted defines intersections as valid units of analysis that are comparable to street segments (Braga, Papachristos, and Hureau 2010). We do not adopt this approach because we believe that intersections are too different from segments to be considered comparable social units (Kim and Hipp 2019). Ancillary analyses constructing datasets with different random placement of the crimes yielded essentially identical results.

For the land use measures, we utilized the NYC Primary Land Use Tax Lot Output (PLUTO) data from the data portal of the Department of City Planning.[2] The business data come from Reference USA (Infogroup 2015). We assigned our crime data, our business data from Reference USA, and our parcel-based land use data to street segments. We then created measures aggregated to three geographic scales: 1) street segments; 2) street segments one street away from the focal segment; 3) street segments two streets away from the focal segment.

Dependent variable

Our dependent variable is a count of the number of robberies that occurred on the street segment during a particular hour of day during the year 2010. Although there are various possible temporal classifications that could be employed (e.g., see Haberman and Ratcliffe 2015), we divided the day into 24 hours and classified a robbery into the hour that it occurred. We then used a nonlinear modeling strategy to account for the change in crime probability over the hours of the day based on the approach of Hipp and Kim (2019). The advantage of this approach compared to strategies that define time periods a priori is that it does not impose a sharp break point for coefficient values between various pre-defined time periods, but rather estimates the change in the parameter as a continuous function of time based on our nonlinear

[2] http://www1.nyc.gov/site/planning/data-maps/open-data.page

parametric function (which is more reasonable). Based on empirical assessment, we determined that a cubic function satisfactorily captures the temporal change in our study area. We parameterize the time effect by creating a variable with values capturing the specific 1 hour periods (thus valued from 0 to 23, starting at midnight). We created quadratic and cubic versions of this measure, and created separate versions of these variables for weekdays and weekends. We also distinguished between crimes on weekdays vs. weekends with an indicator variable that defined the weekend as beginning at 4pm on Friday and ending at midnight on Sunday.

Independent variables

A methodological challenge faced by researchers is how to measure the ambient population potentially generated by retail districts. Scholars have typically adopted one of three strategies for this measurement: 1) the number of establishments in an area (Smith, Frazee, and Davison 2000; Rice and Smith 2002; Bernasco and Block 2011), 2) the number of employees (as a proxy for the ambient population attracted to such locations) (Bowes 2007; Wo 2016) or 3) the proportion of land area devoted to various uses (Ouimet 2000; Smith, Frazee, and Davison 2000; Stucky and Ottensmann 2009; Wo 2019). Whereas measuring the number of establishments presumes that there is something important about the simple presence of such locations, measuring the number of employees is typically adopted as a strategy with the presumption that the presence of more employees is a proxy for the number of patrons of such locations (and therefore does a better job of capturing the ambient population). The measure of land use is conceptually distinct from these two measures, as it not only captures the presence of such establishments, but takes into account their physical size under the presumption that this better captures the physical environment. Despite these conceptual differences, the distinction between these measures is likely less crucial in many research settings as there is typically considerable empirical overlap in these different measures. However, this is arguably not the case in New York City.

We argue that there are indeed conceptual distinctions between measuring the number of employees of businesses and the proportion of land use in a dense environment like New York City. For example, in a high-rise environment, it is possible that a street segment with an even mix of various land usages can still have quite high intensity for any one of those uses. A high rise street in Manhattan can have a relatively low proportion of land use containing retail (given that a high proportion of the high rise building area is residential land use), and yet have a high number of retail employees if the businesses on the ground floor of these buildings are popular. Thus, the proportion of land use in various categories does not convey all the information about such a setting. In contrast, a street with low rise buildings can have a high proportion of retail land use if the buildings are dedicated entirely to this purpose and yet have relatively fewer employees if these are small businesses with few customers. These considerations highlight that in some instances it may be worth distinguishing between these two potential ways of measuring the environment's impact on the ambient population, and we do so here.

We therefore constructed measures of employees and land use at micro-locations. We measured the number of employees in a street segment based on three categories. We used Reference USA data and classified businesses based on 2-digit NAICS codes as the number of employees in: 1) retail (NAICS 2-digit codes 44 and 45); 2) food services (NAICS 2-digit code 71); and 3) total employment. The Reference USA data provide the exact location of these businesses, and the total number of employees for each business, allowing us to directly aggregate them to street segments. Thus, we do not measure specific crime attractors, but rather we use employee measures designed to capture general patterns of ambient population (Andresen

2011). We also constructed measures of the land use characteristics of the segment. Our measures capture the proportion of land use that is: 1) retail; 2) office; 3) factory; 4) garage; 5) storage; 6) other (with proportion residential as the reference category). The empirical evidence in this sample supports that the employees and land use measures are distinct. The correlations between the land use characteristics variables and the employee variables are very modest for the entire sample (the highest values are .11). Within borough the correlations are a bit higher but still quite modest, as the correlation between retail land use and retail employees ranges from .12 to .26 across the five boroughs. Thus, these measures are clearly capturing distinct constructs. Finally, we account for schools, which can increase ambient population, by constructing a measure of the logged number of students attending a school in the street segment.

To capture the size of the population in the local area we constructed a measure of the number of housing units (log transformed); given that we know the parcel location of these units, this measure is more spatially precise than a measure of population from the Census located in blocks. We capture the socio-economic status of the area with a measure of the average value of residential units in the segment. Given prior evidence that aging housing can operate as a proxy for physical disorder and therefore impact crime rates, we included a measure of the average age of housing on the segment (Hipp, Kim, and Kane 2019). We constructed a measure of the percentage of the street segment that is open frontage (which computes the difference between the lot width and the building width for each parcel, and sums them for the segment) under the assumption that such areas might increase crime opportunities. All these measures were initially constructed for parcels, which we directly aggregate to street segments.

We control for various socio-demographic characteristics of the area. These data come from the U.S. Census. For the measures that were available at the block level, we used an imputation technique described by Kim (2016) to place them into street segments. Kim proposed two alternative methods for imputing existing Census block data to adjacent street segments: Simple Average (SA) and Segment Weighted Average (SWA), which relies on apportioning based on the number of residential parcels on a segment face. He found that the two imputation methods are generally valid compared to data actually collected at the street segment level, and thus the simpler method (SA) is preferred. Therefore, we employ the SA method to impute the 2010 Census block data into street segments to measure various socio-demographic characteristics of the area. We also constructed these same measures at the meso-level with an exponential decay surrounding the focal street segment (capped at one mile).

We constructed measures of the racial/ethnic composition (percent black, Latino, and Asian) with percent white and other race as the reference category. Racial/ethnic mixing as racial/ethnic heterogeneity is measured as a Herfindahl index (based on five categories of Black, Latino, Asian, White and other race). We measure disadvantage in the area with the percent single parent households (given that this is the only candidate variable in the Census measured at the block level). The measure of average assessed home value is based on information from the parcel data. We measure residential stability with the percent home owners. Opportunities provided by vacant units are captured with the percent vacant units. We followed the approach of Hipp and Kubrin (2017) in constructing a measure of income inequality in the egohood. This approach uses block group data on the income distribution by racial/ethnic group and combines it with the racial/ethnic composition of each block to impute the income composition in each block. We imputed the income composition of each group to the block level based on the block's racial composition, and then compute the composition of income categories for all blocks in the

0.5 mile egohood. After summing over all blocks in the egohood, we compute the standard deviation of income as the measure of inequality.

Finally, to capture the broader area around a street segment, we follow prior research and constructed measures of structural characteristics within 2.5 miles of the street segment as prior research suggests the broader scale can impact micro crime levels (Hipp, Wo, and Kim 2017; Hipp and Kubrin 2017). We account for potential offenders in the surrounding area with a measure of the population within 2.5 miles, and a quadratic version to capture potential nonlinearities. We also created other measures that might proxy for the presence of more offenders in the broader area: percent aged 16 to 29 (the prime offending ages); percent owners; and percent single person households. Marriage and home ownership may represent a long time horizon that is characteristic of those with more social control (Gottfredson and Hirschi 1990). We account for the socio-economic characteristics of the broader area with a measure of average household income. We measured the income inequality in the 2.5 mile egohood following the same approach as for the 0.5 mile egohood. We created measures of racial/ethnic composition as percent Black, percent Latino, and the racial/ethnic heterogeneity measure.

We present the summary statistics in Table 1 for the five boroughs. As can be seen there, Manhattan has by far the highest population density, as well as the highest density for all three types of employees (retail, food services, and total employment). Whereas Manhattan has an average of 56.6 housing units per street segment (obtained by exponentiating the values in Table 1), Brooklyn has 28.7, the Bronx has 24.9, Queens has 17, and Staten Island has just 10.7. The lowest density by a considerable amount is Staten Island. For total employees, whereas Manhattan has an average of 319 per street segment, Brooklyn has 29, the Bronx has 28, Queens has 17, and Staten Island has 9.

<<<Table 1 about here>>>

Methods

Given the rarity in which more than one robbery event happened on a street segment during one of the hour windows in a particular year, we estimate the models as logistic regression. Just 0.02 percent of segment time periods experienced more than one robbery, therefore estimating anything other than a 0/1 logit model is not feasible. In model 1 we only include the street segment measured variables as a baseline; these measures are then included in all subsequent models. In model 2 we add to model 1 the measures capturing the employee and land use measures from the nearby street segments. In model 3 we add to model 1 the seven measures capturing the day and time of the robbery event. In model 4 we add to model 1 the measures capturing the broader population within 2.5 miles of the segment. And, Model 5 is the full model including all of these measures.

We are interested in assessing the degree of variance explained for these different sets of variables. It is well-known that forward stepping approaches are problematic for assessing the degree of variance explained as the results are dependent on the order in which variables are added to the model. We instead adopt an approach in which we estimate the unique variance explained by the various sets of measures. To accomplish this, we estimate our full model (model 5 from Table 2) and obtain the pseudo r-square from this model. We then estimate a model in which we *exclude* the 7 measures capturing the day and time of the robbery event: the difference between this pseudo r-square and that of the full model is an estimate of the unique variance explained by this set of variables. We adopt a similar strategy for the two other sets of measures (as well as the segment-specific measures). There is no evidence of multicollinearity problems in our models given that our very large sample size improves the precision of the estimates (Goldberger 1991). Although our largest VIF value was approximately 124, when we use O'Brien's approach (O'Brien 2007) to calculate the degree to which the standard errors are inflated we found that a variable with a VIF value of 2 in a sample of 200 would need to have a VIF of 844 in our sample of almost 84,000 segments to equally impact the imprecision of the estimates (Boessen and Hipp 2015). There was no evidence of spatial autocorrelation as the maximum Moran's I value of the residuals did not exceed .05.

Results

Socio-demographic measures

We begin with the baseline model (Model 1), which includes just the variables measured at the level of the street segment. The socio-demographic variables tend to have coefficients in the expected direction. A 20 percentage point increase (approximately one standard deviation) in Blacks, Latinos, or Asians results in increased odds of a robbery by 43%, 39%, and 22%, respectively (exp(.018*20)-1= .43; exp(.016*20)-1= .387; exp(.010*20)-1= .215). The presence of more homeowners—a 30 percentage point increase (approximately one standard deviation)—is associated with 34% decreased odds of a robbery. The percent single parent households have an unexpected negative coefficient, although it is quite small, and the average home value is nonsignificant. However, there is the expected positive relationship for age of housing, which is quite strong as a one standard deviation increase is associated with 23% increased odds of a robbery, consistent with prior research using this measure in Southern California (Hipp, Kim, and Kane 2019). Notably, this measure has a much larger effect than does the average home value effect.

<<<Table 2 about here>>>

Regarding the opportunity variables on the street segment, they tend to have expected effects. A one standard deviation increase in residential units (logged) is associated with 57% increased odds of a robbery. In this study area, the measures of land use by proportion have much stronger effects on robbery location than do the measures of the number of employees. Whereas a one standard deviation increase in the number of retail, food service, or total employees are associated with about 2% increased odds of a robbery, one standard deviation increases in percentage office or retail land use are associated with 22% and 36% increased odds of a robbery, respectively. Garage and storage land use are associated with smaller increases in the odds of a robbery: 6% and 3% respectively. The presence of schools is indeed associated with more robberies, as a one standard deviation increase in students is associated with 5% increased odds of a robbery. The open frontage measure is associated with 9% reduced odds of a robbery for a one standard deviation increase. Consistent with prior studies in the crime and place literature, these micro-scale measures are important as they uniquely explain 12.4% of the variance in the full model (model 5).

Nearby spatial effects

In model 2 of Table 2 we include the meso-level measures of various employee and land use measures (measured as contiguous segments or one additional segment away), as well as the socio-demographic measures of the surrounding area (based on an exponential decay). These measures only modestly improve model fit, as they collectively only uniquely explain 3.4% of the variance of model 5. We do see that the segment-level versions of these variables now have smaller coefficients, suggesting that some of their effect detected in model 1 was due to failing to account for the nearby environment. Nonetheless, the nearby effects are somewhat modest: a one standard deviation increase in retail and food employees in the surrounding segments are associated with increased odds of robberies 1% and 2%, respectively, whereas increases two segments away are associated with 6% and 4% increased odds, respectively. More office and retail land use in surrounding segments is associated with 2% and 9% increased odds of robbery, respectively.

The meso-level socio-demographic variables capturing the nearby area based on an exponential decay show stronger relationships. A 20 percent increase in percent Black or Latino (about one standard deviation) is associated with 30% and 16% increased robbery risk, respectively, whereas a one standard deviation increase in nearby racial/ethnic heterogeneity is associated with 4% increased risk. Income inequality has a relatively strong relationship, as a one standard deviation increase is associated with 12% increased robbery risk. The presence of homeowners in the surrounding area is strongly associated with less robbery risk, as a 20 percent increase is associated with about 50% less robbery risk, whereas more vacancies and population nearby is associated with 3% and 19% more robbery risk, respectively.

Temporal differences

In model 3, we take into account the timing of robbery events by including our six polynomial measures (three for weekdays, and three for weekends), and an indicator variable for weekend days. These measures improve the fit of the model considerably, highlighting the temporality of robbery events. These variables uniquely explain 12.1% of the variance in the final model 5. The marginal effects of these measures are plotted in Figure 1, and show different temporal patterns over weekdays and weekends: on weekdays there is a trough around 6am and a peak at 7pm, whereas on weekends the timing is moved later as the trough is around 10am and the peak is at midnight.

<<<Figure 1 about here>>>

Broader spatial scale effects

In model 4 we include our measures of the surrounding 2.5 miles area around each street segment to capture the broader environment. We find surprisingly strong effects, as the unique variance explained by these measures is 3.7% of the full model, which is slightly more than the unique variance explained by the meso-level measures. We plot the nonlinear effect of population size in Figure 2, which exhibits a slowing positive relationship with robberies. Thus, as the population increases in the surrounding 2.5 miles, the odds of a robbery increase notably. However, this positive relationship slows at higher population levels. The other measures generally show strong effects: a one standard deviation increase in average household income is associated with 12% decreased odds of a robbery, whereas a one standard deviation increase in household inequality or racial/ethnic heterogeneity are associated with 4% and 13% increased odds, respectively. Whereas a one standard deviation increase in percent Black and percent single person households are associated with 15% and 11% increased odds of a robbery, a similar increase in Latinos or owners are associated with 3% and 8% reduced odds.

<<<Figure 2 about here>>>

Full model

Model 5 is the full model with all measures included. The direction and significance of nearly all of the measures remains the same as in the prior models; just a few variables with very small effects in previous models are now nonsignificant. The positive coefficient for racial/ethnic heterogeneity in the street segment is twice as large here as in model 1. But in general, the results are the same as the prior models. One additional point we make is that the combination of both meso- and macro-level measures jointly explain 12% of the variance. Thus, the meso-level measures uniquely explain 3.4% of the variance, the macro-level measures uniquely explain 3.7% of the variance, and excluding both from the final model shows that they share 4.9% of the variance (3.4%+3.7%+4.9%=12%). This is nearly as large as the 12.4% of the variance uniquely explained by the street segment measures, highlighting the important role of these two larger spatial scales in explaining the location of robberies

Interaction models

Finally, we estimated models to assess the extent to which our main effects differ across these dimensions: the temporal context, the nearby context, or the broader context. We accomplished this by creating interaction variables between our segment-level variables and the measures capturing these three dimensions. The model fit improvement was very slight in these interaction models: whereas the pseudo r-square of our full model was .114, the value was .119 or .123 for the models including interactions with time of day or the broader surrounding context. Based on the Bayesian Information Criterion (BIC), the optimal model was the one including interactions with the characteristics of the surrounding 2.5 miles area (BIC= 1,190,066), followed by the model with interactions with the time of day measures (BIC= 1,195,045). However, plotting these interactions revealed that there were only modest bends in the original relationships based on this moderating context, suggesting that the substantive importance of these interactions was limited.

Conclusion

This study has explored the relationship between key characteristics of the social and physical environments and the location of crime in micro-locations at different times of day. By exploiting variability across the large region of New York City, we were able to explore how explanations of robbery location might vary across four particular dimensions: 1) the street segment; 2) the meso-scale surrounding the segment; 3) the temporal pattern of robbery across hours of the day and days of the week; and 4) the macro-scale. An important contribution was comparing the relative importance of these four dimensions. Our findings show that whereas the characteristics of the segment matter for the location of robbery events, the characteristics of nearby segments also have some predictive validity. Nonetheless, we determined that the temporal pattern appeared the most important across these four dimensions. Furthermore, we found that the effects of an even broader spatial scale of population in the surrounding 2.5 miles had much more predictive validity compared to the nearby spatial scale.

Consistent with prior studies, we found that the largest amount of variance explained was captured by the micro-level street segment measures. The fact that some of the segment measures with strong relationships with robberies capture crime opportunities (i.e., more residential population, more office and retail land use) reinforces the insights of crime pattern theory (Brantingham and Brantingham 2008) that crime opportunities play an important role in the location of crime events, including robberies, However, some of these measures capture constructs related to social disorganization theory, including the racial/ethnic composition, the percent owners, and the age of buildings (as a proxy for disorder), highlighting the importance of this perspective even measured at the micro-level. Nonetheless, despite the clear importance of measuring characteristics at the micro-level, the fact that the meso- and macro-level measures combined to explain nearly as much variance as these micro-level measures highlights the importance that researchers not simply focus on characteristics of these micro locations.

An important finding was that there are key differences in robbery risk across the hours of the day and day of the week. This is consistent with the insights of routine activity theory and crime pattern theory, as we would expect the routine activities of persons as they go about their daily lives to lead to temporal regularities in robberies, as observed here (Felson and Boba 2010). Although scholars are aware of the theoretical importance of such temporal patterns, empirical research has less frequently accounted for these patterns while simultaneously assessing spatial patterns of crime. Importantly, this study assessed the relative importance of this temporal pattern compared to micro, meso and macro spatial dimensions, and found that these temporal effects are considerably stronger than the spatial effects. The fact that the routine activities of people differ between weekdays and weekends was reflected in the fact that the hourly patterns were shifted later on weekends compared to weekdays. On weekdays, residents come home earlier from work and there are typically fewer night recreational activities, whereas on weekends there are more frequent late night activities, which increase robbery opportunities. Nonetheless, it is interesting to note that the parameters for the other dimensions in the model changed very little between models including or not including these temporal measures.

A second important finding was that although the meso-level explains less of the unique variance compared to the micro-scale of street segments, it nonetheless is quite important. Consistent with prior studies, there was evidence that the socio-economic composition of the surrounding meso-area, the racial/ethnic composition, and the level of inequality all impacted the robbery risk. These measures all helped in understanding the location of robbery risk, beyond the impact of street segment versions of these measures. This reinforces the message of prior research that the broader meso scale has important consequences, above and beyond what occurs at the micro scale of the street segment (Boessen and Hipp 2015). Nonetheless, the fact that the meso-level scale explained slightly less of the unique variance compared to the macro scale is of particular interest, and implies that researchers would be well served to more carefully consider the broader spatial scale(s) rather than treating it as a nuisance.

Spatial and Temporal Scale in NYC

This leads to our third important finding, which was the relatively large importance of the broader spatial scale for explaining the location of robbery events. Whereas a small body of literature has shown that the city-scale can impact the micro-location of crime (Lyons, Vélez, and Santoro 2013; Velez, Lyons, and Santoro 2015; Peterson and Krivo 2010), our results build on research in Los Angeles showing that the broader spatial scale measured as a 2.5 mile buffer can impact the micro location of robbery (Hipp and Kubrin 2017). This is also consistent with a study of four different cities that showed that the size of the population in a similar broader spatial scale impacted the location of robberies (Hipp, Wo, and Kim 2017). It was notable that our set of measures at this macro scale actually uniquely explained slightly more of the variance than even the set of meso-level measures, highlighting the importance of the macro scale in understanding the location of robbery risk. It is not just the presence of potential offenders in this broader area that seems to matter (as measured by our proxies here), but also the level of income inequality and racial/ethnic heterogeneity; these findings for New York City echo those of earlier research in Los Angeles (Hipp and Kubrin 2017), highlighting that this macro scale appears to have important consequences even when considering micro units within a single city. Whether the macro scale will be as important as the meso scale in other research settings is a useful avenue of future research. It is possible that the high density of New York City enhances the importance of this macro scale, and this importance may not be as pronounced in other city environments with lower density. The fact that several of the parameter estimates for the street segment measures were impacted somewhat by the inclusion of the macro-level measures highlights that these micro-level processes may not operate similarly over all macro environments. An implication is that there is a need for studies with micro-level crime data across many cities to assess the extent to which the macro context may indeed impact such micro-level patterns.

An interesting point is that we were able to compare two different sets of measures of the land use: one set computed the proportion of land use devoted to different uses, whereas the other computed the number of employees on a street segment. We emphasized that whereas these two types of measures may not capture very distinct conceptual differences in many macro settings, in the high density environment of New York City they can actually capture different concepts. Indeed, we demonstrated that the correlation between these two sets of measures was not very high (none more than .26), reinforcing the idea that they capture conceptually different constructs. Our results found that the measures capturing land use proportions were much stronger predictors of the location of robbery events. Thus, understanding what the environment looks like—as captured by the land use proportion measures—appeared more useful than measures based simply on number of employees, which are attempting to proxy for the number of persons in the area (which further proxies for the presence of targets and offenders and guardians).

We acknowledge some limitations to this study. First, although we assessed how characteristics of different macro environments in this city, it is still the case that these are not indicative of all possible macro settings. Given that our results showed the importance of accounting for the characteristics of the macro scale even within one city, it does appear important for future researchers to take into account the macro context. Second, we were often limited to proxy measures of constructs of interest. We did not have actual measures of offenders, targets, or guardians, and hence relied on proxies of the presence of population at different hours of the day. This is a common limitation of much micro crime and place literature, but nonetheless should be kept in mind. Although we tried to account for various important features of the environment that might impact the location of robberies, we acknowledge that there are other possible features for which we did not have measures and may also be important. Similar to most existing studies, another limitation is that we were not able to account for police presence and strategies that are implemented in time and space, which might impact temporal crime patters. We were unable to distinguish between commercial and street robberies, which may exhibit different spatial and temporal patterns. Nonetheless, we do not have any reason to believe that our results would be changed appreciably if we were able to split robberies by commercial and street varieties. Finally, there is always the risk that crime can drive neighborhood change (Skogan 1990), and therefore there may be unaccounted for endogeneity in our models. We acknowledge this risk, although it may be that the impact of crime on our neighborhood measures is relatively slow, and therefore would have more modest consequences for our models. Regardless, this issue should be addressed in future research.

In conclusion, this study has highlighted the importance of considering the micro scale, the meso scale, the macro spatial scale and the temporal scale when studying the spatial distribution of crime. We focused explicitly on robberies, and we found that whereas the micro scale accounted for the largest unique variance explained of these dimensions, the temporal scale was nearly as important, highlighting the importance of temporal patterns for robberies. Furthermore, our results showed that even within this single study area, there was considerable variance explained by taking into account the characteristics of the macro environment defined as a 2.5-mile area around the street segment. This finding parallels other recent work intentionally comparing four macro environments that differed considerably based on micro- and macro-population environment (Hipp, Wo, and Kim 2017). The fact that here we also found such differences even when comparing macro spatial scale in the same metropolitan area (Hipp and Kubrin 2017) indicates that scholars of micro crime and place research would be well served to give more consideration to the macro environment of their study area. The macro-scale, along with the meso-scale, jointly explained nearly as much of the variance in our models as did the micro-scale of street segment measures, highlighting that even when researchers are interested in exploring such micro spatial patterns it is imperative to account for characteristics of the broader area as well.

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Tables and Figures

Table 1. Summary statistics of key variables used in analyses

	Bronx		Brooklyn		Manhattan		Queens		Staten Island	
Logged housing units	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Segment	3.22	2.11	3.36	1.82	4.04	2.51	2.83	1.63	2.37	1.28
One segment away	5.22	2.07	5.44	1.68	6.20	2.40	4.66	1.62	3.91	1.37
Two segments away	6.33	1.98	6.63	1.50	7.43	2.21	5.71	1.59	4.75	1.37
Retail employees (/ 1,000)										
Segment	0.003	0.015	0.004	0.020	0.030	0.165	0.002	0.019	0.001	0.025
One segment away	0.013	0.034	0.018	0.044	0.152	0.419	0.009	0.039	0.005	0.052
Two segments away	0.032	0.061	0.048	0.080	0.435	0.945	0.023	0.069	0.011	0.076
Food employees (/ 1,000)										
Segment	0.002	0.008	0.002	0.009	0.026	0.108	0.001	0.009	0.001	0.008
One segment away	0.009	0.020	0.012	0.023	0.137	0.308	0.007	0.022	0.003	0.016
Two segments away	0.022	0.035	0.033	0.047	0.390	0.716	0.018	0.042	0.007	0.025
Total employees (/ 1,000)										
Segment	0.028	0.143	0.029	0.135	0.319	1.349	0.017	0.109	0.009	0.062
One segment away	0.128	0.314	0.148	0.284	1.603	3.506	0.076	0.242	0.037	0.122
Two segments away	0.313	0.518	0.393	0.541	4.468	8.297	0.190	0.447	0.079	0.183
Segment:										
Percent office land use	0.079	0.203	0.071	0.186	0.161	0.293	0.035	0.118	0.047	0.157
Percent retail land use	0.072	0.179	0.081	0.170	0.070	0.116	0.058	0.160	0.048	0.168
Percent garage land use	0.036	0.129	0.026	0.108	0.027	0.105	0.019	0.088	0.009	0.063
Percent storage land use	0.033	0.133	0.034	0.136	0.026	0.104	0.025	0.114	0.013	0.082
Percent factory land use	0.025	0.119	0.041	0.157	0.003	0.035	0.022	0.111	0.004	0.048
Percent other land use	0.115	0.260	0.096	0.223	0.146	0.262	0.100	0.249	0.090	0.252
Number of segments	11,333		20,099		7,096		32,027		14,080	

Table 2. Models in street segments predicting robbery

	Model 1		Model 2		Model 3		Model 4		Model 5	
Street segment measures	Baseline model		Add nearby spatial measures		Add day/time measures		Add broader spatial measure		Full model	
Percent Black	0.018	**	0.013	**	0.018	**	0.013	**	0.010	**
	(118.34)		(58.57)		(118.44)		(60.22)		(41.17)	
Percent Asian	0.010	**	0.010	**	0.010	**	0.013	**	0.010	**
	(41.55)		(33.76)		(41.57)		(51.29)		(33.00)	
Percent Latino	0.016	**	0.014	**	0.016	**	0.015	**	0.012	**
	(91.85)		(59.42)		(91.94)		(68.67)		(49.48)	
Racial/ethnic heterogeneity	0.108	**	0.242	**	0.107	**	0.190	**	0.225	**
	(5.51)		(10.36)		(5.48)		(8.88)		(9.55)	
Percent single parent households	-0.007	**	-0.002	**	-0.007	**	-0.003	**	-0.002	**
	-(16.12)		-(4.55)		-(16.12)		-(7.74)		-(4.45)	
Percent vacant units	0.000		-0.004	**	0.000		-0.002	**	-0.005	**
	(0.06)		-(9.79)		(0.03)		-(5.44)		-(10.85)	
Percent owners	-0.014	**	-0.006	**	-0.014	**	-0.007	**	-0.005	**
	-(86.65)		-(32.62)		-(86.69)		-(39.31)		-(28.62)	
Residential units (logged)	0.245	**	0.201	**	0.246	**	0.198	**	0.198	**
	(104.01)		(76.97)		(104.12)		(79.23)		(73.77)	
Retail employees (1000s)	0.425	**	0.225	**	0.431	**	0.368	**	0.229	**
	(20.10)		(8.98)		(20.08)		(17.43)		(9.23)	
Food service employees (1000s)	0.721	**	0.386	**	0.727	**	0.798	**	0.441	**
	(15.88)		(7.12)		(15.90)		(17.81)		(8.32)	
Total employees (1000s)	0.041	**	0.002		0.041	**	0.034	**	0.001	
	(8.42)		(0.37)		(8.38)		(7.24)		(0.21)	

Proportion office land use	1.130	**	0.696	**	1.133	**	0.879	**	0.641	**
	(63.72)		(30.72)		(63.77)		(48.03)		(28.09)	
Proportion retail land use	1.883	**	1.406	**	1.888	**	1.724	**	1.338	**
	(109.36)		(62.67)		(109.45)		(97.55)		(58.79)	
Proportion garage land use	0.598	**	0.435	**	0.600	**	0.268	**	0.340	**
	(17.28)		(10.81)		(17.29)		(7.59)		(8.33)	
Proportion storage land use	0.287	**	0.420	**	0.288	**	-0.028		0.336	**
	(8.47)		(10.14)		(8.49)		-(0.81)		(8.08)	
Proportion factory land use	-0.064	†	0.121	*	-0.063	†	-0.431	**	0.026	
	-(1.68)		(2.53)		-(1.67)		-(11.19)		(0.54)	
Proportion other land use	0.740	**	0.517	**	0.742	**	0.542	**	0.466	**
	(46.64)		(27.49)		(46.68)		(33.19)		(24.55)	
Open frontage	-0.131	**	-0.087	**	-0.131	**	-0.058	**	-0.081	**
	-(18.99)		-(10.67)		-(18.98)		-(9.20)		-(10.13)	
Average age of buildings	0.009	**	0.006	**	0.010	**	0.005	**	0.004	**
	(61.08)		(39.26)		(61.14)		(30.25)		(27.88)	
Average home value	0.000		0.000	**	0.000	†	0.000		0.000	*
	(1.64)		(3.46)		(1.66)		-(0.23)		(2.57)	
Number of school students	0.026	**	0.025	**	0.026	**	0.020	**	0.023	**
	(18.88)		(18.32)		(18.93)		(14.47)		(16.30)	
Neighborhood measures										
Percent Black			0.013	**					0.007	**
			(30.01)						(14.10)	
Percent Asian			-0.001	†					0.003	**
			-(1.68)						(4.54)	

Percent Latino				0.007	**								0.009	**
				(15.31)									(16.26)	
Racial/ethnic heterogeneity				0.161	**								-0.049	
				(4.30)									-(1.07)	
Percent single parent households				-0.030	**								-0.018	**
				-(26.67)									-(13.69)	
Percent vacant units				0.006	**								0.010	**
				(3.37)									(5.38)	
Percent owners				-0.026	**								-0.015	**
				-(75.66)									-(32.91)	
Population (logged)				0.040	**								0.000	
				(12.80)									(0.03)	
Income inequality				1.240	**								1.144	**
				(26.31)									(19.28)	
Nearby spatial measures														
Retail employees one segment away (1000s)				0.035	*								0.041	**
				(2.24)									(2.67)	
Food service employees one segment away (1000s)				0.200	**								0.183	**
				(6.22)									(5.84)	
Total employees one segment away (1000s)				0.002									0.004	
				(0.69)									(1.17)	
Retail employees two segments away (1000s)				0.112	**								0.119	**
				(13.96)									(14.83)	
Food service employees two segments away (1000s)				0.088	**								0.123	**
				(6.93)									(9.80)	
Total employees two segments away (1000s)				-0.012	**								-0.013	**
				-(7.87)									-(8.47)	

Proportion office land use one segment away				0.130	**								0.133	**
				(4.99)									(5.06)	
Proportion retail land use one segment away				0.532	**								0.622	**
				(16.53)									(18.78)	
Proportion garage land use one segment away				-0.459	**								-0.490	**
				-(7.42)									-(7.79)	
Proportion storage land use one segment away				-0.957	**								-0.930	**
				-(17.65)									-(16.93)	
Proportion factory land use one segment away				-0.601	**								-0.731	**
				-(10.79)									-(12.95)	
Proportion other land use one segment away				-0.002									-0.001	
				-(0.09)									-(0.04)	
Open frontage one segment away				0.012	**								0.021	**
				(5.44)									(9.76)	
Average home value one segment away				-0.017	**								-0.013	**
				-(19.13)									-(15.42)	
Day/time measures														
Weekend							0.480	**					0.481	**
							(26.18)						(26.22)	
Hour (weekend)							-0.316	**					-0.317	**
							-(48.36)						-(48.36)	
Hour (weekday)							-0.378	**					-0.378	**
							-(79.34)						-(79.27)	
Hour squared (weekend)							0.021	**					0.021	**
							(31.11)						(31.11)	
Hour squared (weekday)							0.042	**					0.042	**
							(85.26)						(85.20)	

Hour cubed (weekend)							-0.358	**					-0.359	**
							-(18.68)						-(18.69)	
Hour cubed (weekday)							-1.138	**					-1.139	**
							-(81.08)						-(81.02)	
Broader spatial area (surrounding 2.5 miles)														
Population										0.941	**		0.889	**
										(45.64)			(42.46)	
Population squared										-0.191	**		-0.179	**
										-(37.22)			-(34.59)	
Average household income										-0.379	**		-0.354	**
										-(8.21)			-(7.05)	
Income inequality										0.461	**		0.031	
										(4.66)			(0.29)	
Racial/ethnic heterogeneity										1.180	**		1.234	**
										(23.38)			(20.71)	
Percent owners										-0.005	**		0.003	*
										-(4.48)			(2.20)	
Percent Black										0.011	**		0.012	**
										(30.41)			(27.72)	
Percent Latino										-0.002	**		-0.002	**
										-(5.59)			-(5.13)	
Percent aged 16 to 29										0.013	**		0.001	
										(4.96)			(0.56)	
Percent single persons										0.017	**		0.008	**
										(10.82)			(4.52)	

Spatial and Temporal Scale in NYC

Intercept	-7.145	**		-7.898	**		-6.812	**		-8.246	**		-8.010	**
	-(290.21)			-(145.04)			-(252.67)			-(52.71)			-(48.39)	
Pseudo r-squared	0.087			0.096			0.100			0.096			0.114	
BIC	1236132			1223785			1217531			1223023			1199582	
Percent unique variance explained	12.4%			3.4%			12.1%			3.7%				

*Note: ** p < .01; * p < .05. T-values in parentheses. N = 14,110,656 (83,992 street segments X 24 hours X 7 days)*

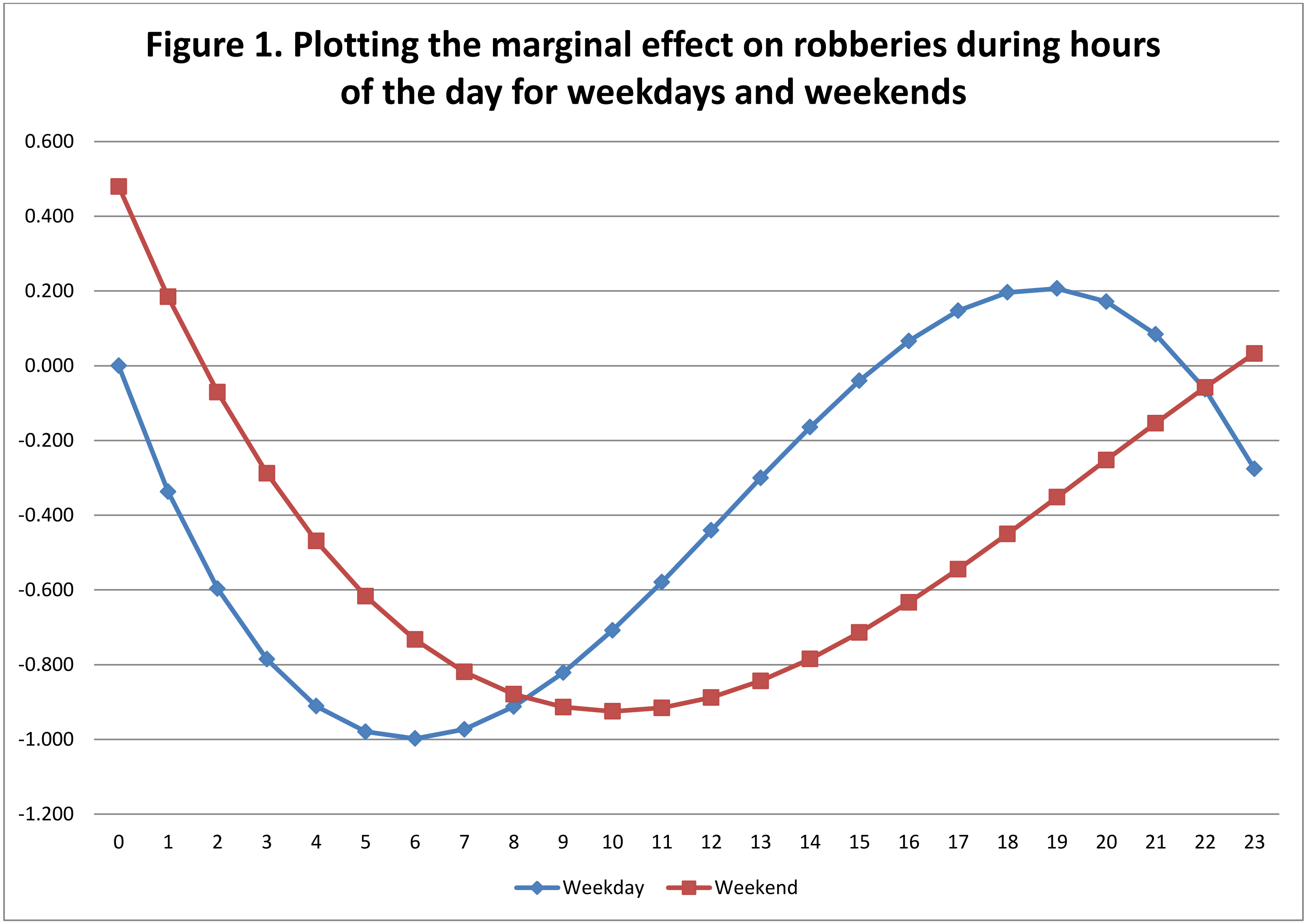
Figure 1. Plotting the marginal effect on robberies during hours of the day for weekdays and weekends
0.600
0.400
0.200
0.000
-0.200
-0.400
-0.600
-0.800
-1.000
-1.200
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
Weekday
Weekend

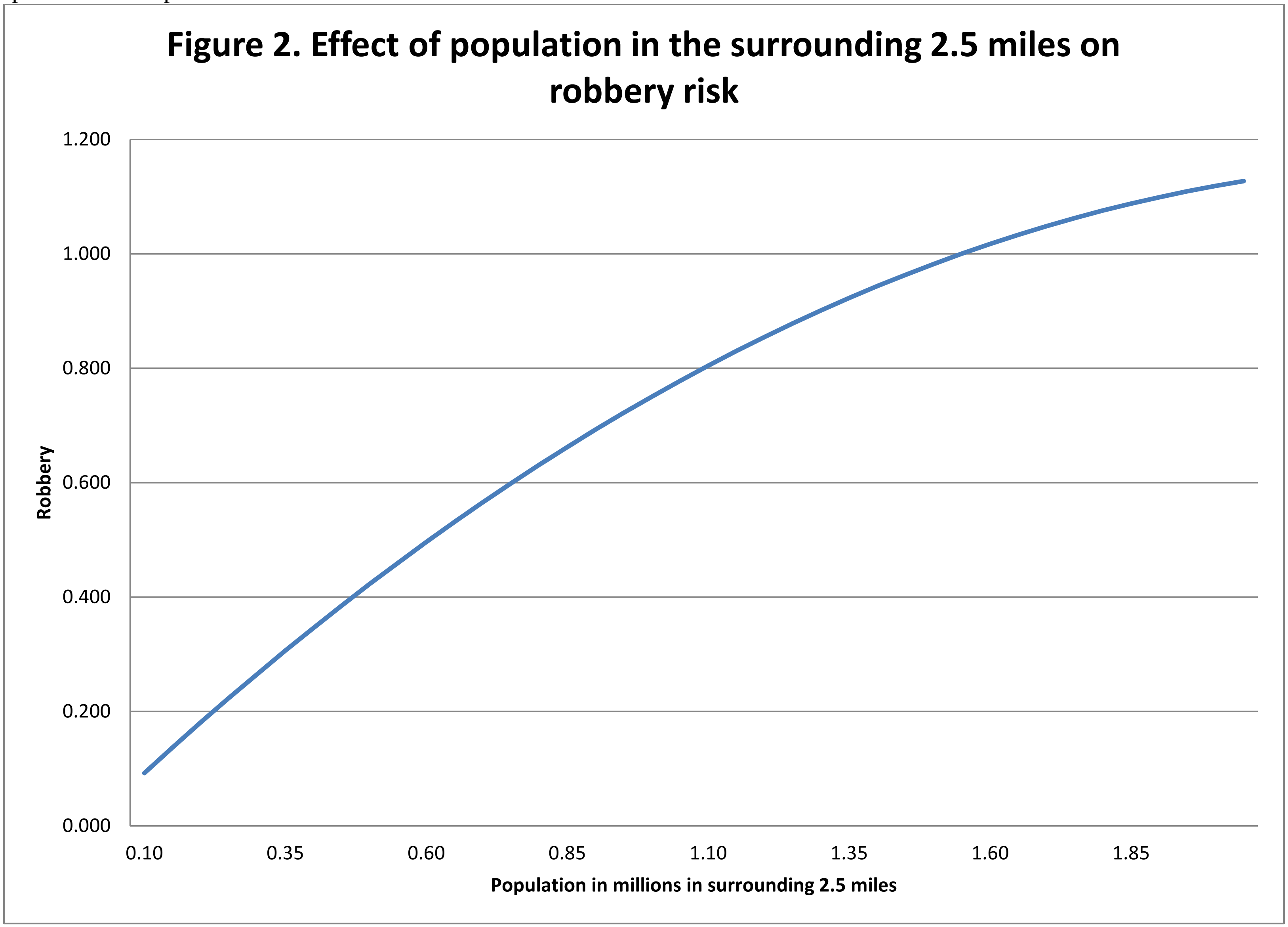
Figure 2. Effect of population in the surrounding 2.5 miles on robbery risk
1.200
1.000
0.800
0.600
0.400
0.200
0.000
Robbery
0.10
0.35
0.60
0.85
1.10
1.35
1.60
1.85
Population in millions in surrounding 2.5 miles