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Abstract

Criminological theories have posited that the built environment impacts where crime occurs, however measuring the built environment is difficult. Furthermore, it is uncertain whether the built environment differentially impacts crime in high disadvantage neighborhoods. This study extracts features of the built environment from Google Street View images with a machine learning semantic segmentation strategy to create measures of fences, walls, buildings, and greenspace for over 66,000 street segments in Los Angeles. Results indicate that the presence of more buildings on a segment was associated with higher crime rates, and had a particularly strong positive relationship with robbery and motor vehicle theft in low disadvantage neighborhoods. Notably, fences and walls exhibited different relationships with crime. Walls, which do not allow visibility, were strongly negatively related to crime, particularly for robbery and burglary in high disadvantage neighborhoods. Fences, which allow visibility, were associated with fewer robberies and larcenies, but *more* burglaries and aggravated assaults. Fences only exhibited a negative relationship with violent crime when they were located in low disadvantage neighborhoods. The results highlight the importance of accounting for the built environment and the surrounding level of disadvantage when exploring the micro-location of crime.

Keywords*:* *Built Environment, Crime, Google Street View, Machine Learning, Semantic Segmentation*

Bios

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

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How concentrated disadvantage moderates the built environment and crime relationship on street segments in Los Angeles

There is a long-standing interest in the location of crime across urban environments, and scholars have generally focused on both the social and physical dimensions of the environment. A challenge is that despite some difficulties of measuring social dynamics, measuring the physical environment is often more difficult than measuring the social dimensions of residents living in an area. Whereas research has utilized strategies such as surveys of residents, field surveys, or using administrative data, these useful strategies nonetheless have limitations when measuring the built environment, including the types of features that can be measured or the size of the study area that is feasible. As a consequence, the recent development of high-quality images of the built environment available on the web from sources such as Google Street View (GSV) since 2007 combined with advances in machine learning techniques to detect features in images have enabled measuring distinct features in larger study areas. A recent study used such a strategy in the mid-sized city of Santa Ana, CA to explore how features of the built environment are related to street segments with more crime (Hipp et al. 2021).

We build on this recent research and study how the built environment in Los Angeles city is related to crime levels on street segments, with two broad goals. First, this project allows us to assess the robustness of the findings of a previous study of the mid-sized city of Santa Ana (Hipp et al. 2021), and compare them to the findings of the very large city of Los Angeles. A limitation of single-city studies is that there is uncertainty regarding the extent to which the results can generalize to other cities, and therefore assessing how the built environment is related to crime in a second city as we do here can provide important insights. Furthermore, although earlier techniques to measure the built environment through audits or surveys were constrained to small geographic scale studies, it is straightforward for a machine learning strategy using GSV to scale up to a very large city with over 66,000 street segments.

An even more important broad second goal of the present study is to assess whether the relationships between these built environment features and crime are robust across low and high disadvantage neighborhoods. Recent scholarship has explored whether features of the environment impact crime differently in low versus high poverty neighborhoods. This literature is based on the idea that the neighborhood context can impact the presence of offenders or guardians, and therefore this has consequences based on the local opportunities that the physical environment might create (Hipp 2016; Wilcox, Land, and Hunt 2003). More broadly, this is an important question as it could provide insight on potential context-specific strategies for improving the built environment. Given the diversity of neighborhoods throughout Los Angeles, it is particularly well-suited to this particular research question.

The paper takes the following course. In the next section we describe three key theories that describe how features of the built environment may impact the micro-location of crime, and describe four broad categories of features that we focus on, and how they may exhibit nonlinear relationships with certain types of crime. In that section, we consider how the effect of these built environment features may differ across low and high disadvantage neighborhoods. Following that, we describe our data and our methodological approach for capturing and classifying GSV images. We present the results of the models using our built environment measures to explain the level of crime in street segments of this city and assess nonlinearity. We then test interactions of these measures with concentrated disadvantage, and then conclude with a discussion of the implications of the results.

Literature review

Measuring the built environment

Given the interest in how the built environment can impact the location of crime, recent scholarship has explored various ways to measure the built environment. One challenge is that many features of the built environment cannot be captured with administrative data. Strategies using surveys of residents or field experts are costly and therefore limited in geographic scope, and therefore an alternative strategy utilizes virtual neighborhood audits with open-source street view imagery data such as Google Street View (GSV) data (Gong et al. 2018; He, Páez, and Liu 2017; Odgers et al. 2012). However, when using manual evaluation methods these studies have limited geographic scope, and therefore a recent advance is to utilize machine learning technologies to analyze GSV data using deep neural networks such as AlexNet and Inception-v3 (Kang and Kang 2017; Zhang et al. 2019). One study used the Google Vision API to classify various objects in the environment and assessed how this is related to crime diversity on street segments (Khorshidi et al. 2021).

A recent study by Hipp and colleagues (Hipp et al. 2021) demonstrated the importance of capturing a range of detailed streetscape elements based on three key theories that explain why various physical features of the environment might impact where crime occurs: crime prevention through environmental design (CPTED), crime pattern theory, and routine activity theory. The CPTED perspective explicitly focuses on how micro-level features of the built environment can either enhance or inhibit crime by impacting potential guardianship capability (Newman 1972). Some features of the environment can limit visibility, which reduces the ability of guardianship, whereas other features can create a sense of responsibility for an environment through boundary creation, etc. (Newman 1972). In crime pattern theory, street patterns, street features, and the general layout of an environment are the "backcloth" that impacts the spatial patterns of potential offenders and targets (Brantingham and Brantingham 2008). Locations that attract a number of people can serve as crime generators (Bernasco and Block 2011; Boessen and Hipp 2018) and those that disproportionately attract offenders serve as crime attractors (Kinney et al. 2008; Ratcliffe 2011). In routine activity theory, it is the convergence in time and space of offenders, targets, and a lack of guardians that increases the likelihood of a crime occurring, and the physical environment can impact this in various ways, similar to the backcloth of crime pattern theory (Felson 2002). Hipp and colleagues (2021) utilized these theories in their study that measured built environment features within four broad categories in the city of Santa Ana, CA: 1) vibrancy, 2) auto-oriented, 3) defensible space created by fences and walls, 4) greenspace. We utilize the same four categories in the present study of Los Angeles—the second largest city in the U.S.—to explore whether their relationships with crime on street segments are similar in this city.

For many of these features of the built environment there are possible nonlinear relationships with crime. This is because these features are posited to impact the combination of targets, offenders, and guardians in an environment, which does not lead to straightforward linear hypotheses. Indeed, Hipp and colleagues (2021) posited and found such nonlinear patterns in their study of the city of Santa Ana. For example, an environment that is moderately vibrant based on buildings or humans would likely have more crime due to increased opportunities, but at some point a critical mass occurs and higher levels of vibrancy provide enough guardians to reduce crime levels (Browning et al. 2010). Likewise, there can be saturation effects where features such as fences or walls that provide protection at moderate levels may not be any more beneficial at very high concentrations.

Throughout the following section we also consider how concentrated disadvantage might moderate these effects. Research attempting to integrate routine activity and social disorganization theories has posited that there may be interaction effects in which various measures capturing local opportunities for crime may differentially impact crime risk depending on the neighborhood environment (Stark 1987; Stucky and Ottensmann 2009; Wilcox, Land, and Hunt 2003). One possibility is that if the surrounding neighborhood has lower levels of informal social control capability (Sampson and Groves 1989; Wickes et al. 2017), this will translate into lower guardianship at such locations. This would imply that measures capturing opportunities will result in more crime if there is less local guardianship. Alternatively, the presence of nearby potential offenders may interact with opportunity locations to yield more crime (Hipp 2016). If more disadvantaged neighborhoods have more offenders, as posited in the initial specification of social disorganization theory (Shaw and McKay 1942), this would imply that crime opportunities in such neighborhoods would translate into more crime. A countervailing possibility is a saturation effect in which disadvantaged neighborhoods already have high crime levels, and therefore further opportunities would not so strongly impact the location of crime (Hannon 2002). It is unclear which of these patterns we should expect, and in the next section we consider how each of these built environment features might operate differently in high versus low disadvantage environments.

Key features of the built environment

One important consequence of the built environment of an area is that it might either promote or dampen the vibrancy of the area. Jane Jacobs (Jacobs 1961) posited that this vibrancy can provide potential guardianship to make a location safer, as routine activity theory suggests. Prior research has explored this idea, such as testing and finding a nonlinear relationship between business parcels and crime levels (Browning et al. 2010), or testing whether the number of businesses or employees in an area are related to the level of crime (Bernasco and Block 2011; Hipp, Wo, and Kim 2017), or using detailed land use data about the types of businesses present (Bowers 2014; Stucky and Ottensmann 2009). However, these strategies do not provide fine grained information about the actual spatial layout of businesses. Using GSV images allows us to distinguish between a downtown location in which the buildings front onto the street (allowing walkability) versus malls or strip malls in which large parking lots front the street and patrons typically arrive by vehicle. We are also able to assess the extent to which humans are present in the environment. It is uncertain what impact a vibrant location will have on crime (Hipp and Kim 2019): whereas Jacobs (1961) posited that vibrant locations will have less crime given the greater presence of guardians, routine activity theory implies that such locations will also have more targets and offenders, which will create more crime opportunities and therefore more crime.

It is not clear how the level of concentrated disadvantage in an area might moderate the relationship between vibrancy and crime. On the one hand, if neighborhoods with concentrated disadvantage have more potential offenders nearby (Shaw and McKay 1942) then the vibrancy would imply more potential targets about and therefore result in a stronger positive relationship between vibrancy and crime, particularly crimes such as robbery and motor vehicle theft. On the other hand, the presence of more people in a vibrant area could imply more potential guardians, which could have a negative effect on these crime types. The implication would be that vibrancy could have a stronger negative effect on crime in more disadvantaged neighborhoods. We will assess these competing perspectives here.

In contrast to vibrant environments, some characteristics imply an auto-oriented environment. The explicit presence of vehicles in the environment is a direct measure of an auto-oriented environment whereas the presence of more pavement in images will often capture the impervious surface parking areas for parcels set back from the street. These impervious surfaces arguably create a less inviting environment, resulting in fewer guardians lingering in the location (Jacobs 1961). Given the evidence that more disadvantaged communities tend to have more pavement and less greenspace, this feature may be particularly important in more disadvantaged locations. Furthermore, if there are more potential offenders in disadvantaged neighborhoods, then we would expect the positive relationship between an auto-oriented environment and crime to be particularly strong in more disadvantaged neighborhoods.

An important feature of the built environment is the ability to enhance defensible space (Newman 1972), and fences and walls may be particularly important in this regard. These barriers can make accessing a location more difficult. Despite their potential importance, walls and fences are rarely included in models given the difficulty of measuring them. An important distinction between fences and walls is their impact on the visibility of the environment, and how CPTED theory posits that this can enhance guardianship behavior. Thus, fences typically still allow visibility—such as picket, chain link, or wrought iron fences—whereas walls block visibility. Hipp and colleagues (2021) demonstrated that these two measures could have different impacts on crime in their study site.

A further question is whether the impacts of walls and fences on crime are moderated by the level of concentrated disadvantage in the environment. If there are more potential offenders nearby in disadvantaged areas, as well as more crime in general, then the expected protective effect of walls and fences may be stronger in more disadvantaged neighborhoods. In this view, the guardianship capability that these features provide would have less effect in low disadvantage environments in which there is less crime overall, but a more pronounced effect in high disadvantage environments.

A final key feature of the built environment is greenspace, as urban studies scholars have shown evidence that the presence of vegetation in an area (such as trees and shrubbery) can make it more desirable, which may foster more neighborhood attachment (Lee et al. 2008), higher home values (Kestens, Thériault, and Rosiers 2004) and consequently more potential informal social control capability. It may also encourage residents to walk more which can improve physical health in addition to creating more potential social interaction in the neighborhood and increasing potential guardians (Rogers et al. 2010; Sung and Lee 2015). On the other hand, the CPTED literature posits that shrubbery near homes can increase crime opportunities to the extent that it provides cover for offenders (Patino et al. 2014). Indeed, a prior study of the city of Santa Ana found an inverted-U shaped relationship in which the lowest levels of aggravated assault and motor vehicle theft occurred in environments with either very little, or very much, vegetation (Hipp et al. 2021).

The presence of open green areas may also create a more desirable environment. The presence of greenspace may encourage more outdoor activity: as a consequence, studies of parks argue that they can act as gathering places that can increase neighborhood cohesion and guardianship capability (Cohen, Inagami, and Finch 2008; Hipp et al. 2014). Although this greenspace might increase neighborhood social interaction and cohesion, it could also bring about more potential conflict and crime opportunities. Furthermore, a risk with open green areas as a public gathering place is that the groups of people that gather there can vary. These competing perspectives are seen in the literature in which some studies have found higher levels of crime in parks (Kim and Hipp 2017) but other studies find that this relationship depends on the characteristics of the park (Groff and McCord 2011; Kimpton, Corcoran, and Wickes 2017). Hipp and colleagues (2021) measured this greenspace more generally, and found that they tended to have more crime in the study city of Santa Ana.

As a consequence, in more disadvantaged neighborhoods with more gangs, parks and greenspace may serve as gathering spaces for gang members, which may lead to higher levels of crime nearby, particularly violent crime. Nonetheless, it is worth noting that one study focusing on parks—rather than greenspace more generally—found that the positive relationship between concentrated disadvantage and aggravated assault disappeared in street segments with parks; instead, parks were associated with higher aggravated assault rates when they were located in *low* disadvantage neighborhoods (Boessen and Hipp 2018). In the present study we focus on greenspace specifically, and not parks more generally, though we note that studies have consistently found that more disadvantaged neighborhoods have fewer trees, leading to less shade and more exposed environments (Garrison 2018; Li, Zhang, Li, Kuzovkina, et al. 2015). One possibility is that the relatively few disadvantaged locations with vegetation will appear to have more cohesiveness among residents—given presumed greater care towards the environment—and therefore experience less crime. The implication would be a stronger negative effect for this feature in more disadvantaged neighborhoods. We will explore in this study whether this is the case for greenspace more generally.

Data and Methods

Study area

The study site is the city of Los Angeles. This is the second largest city in the U.S., and contains a range of built environment settings from the dense downtown to the suburban San Fernando Valley in the northwest portion and therefore provides an excellent study location. We use street segments as the units of analysis, which contain both sides of a street between two street intersections, given that prior scholars have argued that they are an appropriate geographic unit for studying social processes (Taylor 1997; Weisburd, Groff, and Yang 2012). We constructed a street segment-level dataset by combining crime data from the Los Angeles Police Department, socio-demographic statistics from the U.S. Census, and business establishment information from Reference USA Historical Business Dataset (Infogroup 2015). To precisely measure the built environment at the segment level, we used images collected from GSV that were coded and aggregated to street segments as explained in detail below.

Dependent variables: counts of crime events

Our dependent variables are counts of five serious crime types (aggravated assaults, robberies, burglaries, motor vehicle thefts, and larcenies) that occurred on a street segment during 2017-2019. The crime data were provided by the police agency at the 100 block to avoid privacy disclosure. Since we do not know the exact address, we used a multiple imputation strategy to assign crime incidents to street segments. We do not know the last two digits of the address, so we needed to randomly assign values. We used a specific random assignment and chose 11 possible values for the last two digits that spanned the range of possible values, but were split between even and odd numbers. Thus, we created 11 duplicates for each crime observation and assigned them the following last two digits: 01, 09, 20, 29, 40, 50, 59, 70, 79, 90, and 99.[1] This provides us a range of possible addresses along the street, and we then

[1] For example, consider crime incidents labeled with the address of 4XX Main Street. We would create 11 addresses: 401 Main St.; 409 Main St.; 420 Main St.; 429 Main St.; 440 Main St.; 450 Main St.; 459 Main St.; 470

geocoded these in ArcGIS, with a geocoding match rate of 96.6%. We assigned the geocoded address to the appropriate street segment and then computed the proportion of the 11 assigned addresses for an incident that are assigned to each segment: in 65% of cases all 11 points are assigned to a single street segment, and any crime incident on this 100 block is assigned to that specific segment. In cases in which the points are assigned to more than one segment (typically two, but on rare occasions more) we assigned the crime to a particular segment based on the proportionate probability based on the proportion of 11 addresses assigned to the segment. We aggregated the counts for the five serious crime types to street segments.

Collecting GSV images

We used panoramic GSV images to measure the micro-level built environment characteristics in Los Angeles. Although prior studies have used various intervals to collect images, we follow the suggestions from the results of Kim and colleagues (Kim et al. 2021) and used 20 meter intervals. At each point we pulled the panoramic image using the GSV API; we did not have images for 13.4% of segments either because of limited access to some properties (e.g., gated communities) or because there were no images between 2017 and 2020. Based on the GSV metadata API, 93.9% of the images were taken between 2017 and 2020, and therefore we limited our extraction to images from this time period. As done in previous studies using GSV, we also avoided using images from points located near street intersections to make sure that the images used reflect the environment of a single segment. After these exclusions, the

Main St.; 479 Main St.; 490 Main St.; and 499 Main St. We then geocode each of these addresses and place them on the appropriate street segment. Suppose that 7 are located on street segment A and 4 are located on street segment B. Then the probability of a crime incident with the address of 4XX Main St. has a .636 probability of having occurred on segment A (7/11 = .636) and a .364 probability of having occurred on segment B (4/11 = .364). If 12 crimes actually occurred during the study period at 4XX Main St., we place each crime on either segment A or B based on these probabilities.

total number of images used in this study is 432,684 for 66,844 road segments (a length of 172 meters on average), and an average of 6.47 GSV acquisition points per segment.

Prior research has pointed out some distortion in the upper and lower portions of GSV panoramic images (Tsai and Chang 2013; Yin et al. 2015). Accordingly, the central portion with less distortion provides more useful information, as this portion is more consistent with the pedestrian's point of view (Xia, Yabuki, and Fukuda 2021; Yin and Wang 2016). We therefore alleviated the distortion in images by excluding 100 pixels from each of the upper and lower parts of the panoramic image, leaving us with the 76% of the center of the image.

Machine learning to analyze the images: semantic segmentation

We analyzed the images using semantic segmentation, a technique that uses deep learning from computer vision to classify each pixel as an image component. Rather than simply using a color band of an image to extract image elements (Li, Zhang, Li, Ricard, et al. 2015), we follow Lu's (2018) proposed semantic segmentation strategy employing deep learning to classify the image components not only based on pixel color but also by taking into account the distribution and shapes of components. Several segmentation models exist for street image analysis in the literature, including FCN8s (Long, Shelhamer, and Darrell 2015), SegNet (Badrinarayanan, Kendall, and Cipolla 2017), and PSPNet (Zhao et al. 2017); however, we employed the Deeplabv3+ model (Chen et al. 2018) given its solid performance in prior research with various datasets[2]. It has been used in several studies for image processing (e.g., Du, Ning, and Yan 2020; Liu et al. 2019; Wang and Vermeulen 2020).

[2] https://github.com/lexfridman/mit-deep-learning

The Deeplabv3+ model was pre-trained with the ‘Cityscapes’ dataset (Cordts et al. 2016)[3], and numerous studies have used the Cityscapes dataset for training deep learning models and applied these algorithms to various study areas (Du, Ning, and Yan 2020; Krylov, Kenny, and Dahyot 2018; Yang et al. 2019). Based on the trained model, we used the following eleven elements of the built environment: buildings, humans, sidewalks, vehicles, pavement, fences, walls, terrain (e.g., grassy areas), vegetation (e.g., trees and shrubbery), objects (e.g. pole, traffic sign, traffic light), and sky.[4] We calculated the percentage of each of these elements in each panoramic image.

We present some example images in Figure 1 to demonstrate what the built environment looks like in cases with relatively high values on a particular element. Figure 1a shows an example image in which vehicles parked along the curb results in a relatively high proportion of vehicles (in addition to images with many autos actually driving). The pavement is also prevalent due to the street, but Figure 1b demonstrates that pavement captures impervious surfaces more generally, and therefore also captures large parking areas. There is a high proportion of sky, which contrasts with Figure 1c in which the abundant trees result in a high proportion of vegetation along with a low proportion of sky. Another way there can be a low proportion of sky occurs when there are many buildings, and Figure 1d shows an image with a number of high rises in the environment. Figure 1e demonstrates that fences are features that one can see through, and also shows the pavement captured in a parking lot, whereas Figure 1f demonstrates that walls do not allow visibility through them.

[3]Source: Cityscapes website, https://www.cityscapes-dataset.com/dataset-overview/#labeling-policy (accessed on Jan. 28, 2020)

[4] Deeplab3+ extracts 19 elements in total. Given that we anticipated very few trains in our images, we had 18 elements. We also collapsed elements that are similar conceptually: “person” and “rider” are collapsed into the category of humans; “car”, “truck”, “bus”, “motorcycle”, and “bicycle” are collapsed into vehicles; “poles”, “traffic signs”, and “traffic lights” are collapsed into objects.

<<<Figure 1 about here>>>

Control variables

We also accounted for several measures of the environment that prior research has shown are related to the spatial distribution of crime incidents. The measures capturing socio-demographic characteristics come from the U.S. Census in 2010 for variables in blocks, and the American Community Survey 5-year estimates (2008-12) for variables in block groups, and are constructed using an exponential decay centered on each street segment.[5] This method better captures the neighborhood environment of a segment, as the segment itself is too small for socio-demographic characteristics and using a larger Census geographic unit such as a block group or tract does not capture the environment explicitly surrounding a segment. For block-level variables it is straightforward to create buffers based on an exponential decay around the segment (including the segment itself). For variables only available at the block group- or tract-level, we imputed them to blocks before applying this method with the buffer measures. We utilized a synthetic ecological inference approach that enables us to impute the data based on other characteristics of the block, which is a more principled strategy than simple area-based imputation (Boessen and Hipp 2015).

We measured *concentrated disadvantage* through a principal factor analysis that combines the following variables into a factor score: percent at or below 125% of the poverty level, mean household income, percent with at least a bachelor's degree, and percent single parent households. Similarly, *residential stability* was measured by combining percent owners, percent living in the same house 5 years ago, and average length of residence. The racial/ethnic composition was measured as *percent Black*, *percent Asian*, and *percent Latino*, leaving percent

[5] These data are in blocks, and the exponential decay is computed in a ½ mile buffer around a focal block. There are adjacent blocks with these buffer values for a segment, and we compute the average value of the buffers (they are extremely highly correlated).

White and other race as the remaining category. A measure of *racial/ethnic heterogeneity* was created as a Herfindahl index combining the racial/ethnic categories as a sum of squared proportions, and then subtracted from 1. Additionally, the *percent occupied units* and the *percent aged 16 to 29*, as prior research suggests they might be associated with crime.[6]

We created opportunity variables at the street segment level using business establishment data from the Reference USA Historical Business Dataset. We geocoded the exact location of the business establishments and aggregated them to the street segment. We created a measure of *consumer-facing employees* to capture both workers and possible patrons of retail and food establishments.[7] We also computed the *non-consumer employees* (subtracting the consumer-facing employees from total employees) (Hipp and Luo 2022). We constructed a measure of *logged population* in the segment (after adding 1), by using Census population counts in blocks and apportioning them to street segments by employing the approach described in Kim (2018). We also constructed spatial lags of these variables with an inverse distance decay capped at 0.5 miles around the segment without including the segment itself. Finally, we created an indicator variable with a value of 1 if the segment was a residential block (at least 50% of the land area was residential units), and 0 otherwise. This allows distinguishing between residential and non-residential blocks in the analyses.

Table 1 presents the descriptive statistics of the variables. For our measures of vibrancy, buildings constitute 5% of these images, on average, sidewalks are 3% and humans are just 0.1%. For the auto-oriented measures, about 3% of the image is vehicles and 19% is pavement. Fences and walls are each about 1%, on average. Regarding the measures of greenspace, 22% is

[6] An alternative measure would capture the percentage of *males* aged 16 to 29 given that they are more involved in offending. However, such a measure is extremely similar to measuring the total population aged 16 to 29: we constructed tract-level measures of each and they were correlated .93.
[7] These are workers for firms classified by the 2-digit NAICS codes of 44, 45, 71, and 72.

vegetation and 2% is terrain. In Table 2 we present the correlations of the independent variables in our models. We see that there are generally quite modest correlations among our GSV measures, as well as the variables in general. Of interest, we see that there is a negative -.49 correlation between concentrated disadvantage and vegetation, consistent with earlier research showing less vegetation in more impoverished neighborhoods. There is a correlation of about .5 between the two measures of employees in the surrounding area and the GSV measure of buildings, highlighting that this measure, while somewhat capturing businesses, is also capturing unique information about the built environment.

<<<Tables 1 and 2 about here>>>

Methods

Our outcome crime count variables exhibited overdispersion and we therefore estimated negative binomial regression models. The model is written as:

$$E(y) = exp(\alpha + B_1\boldsymbol{X} + B_2\boldsymbol{S} + B_3\boldsymbol{E} + B_4\boldsymbol{WE} + \nu) \quad (2)$$

where y is the number of crime events for each crime type, α is an intercept, $\boldsymbol{X}$ represents the GSV built environment variables, $\boldsymbol{S}$ contains the structural characteristic variables including socio-demographics, $\boldsymbol{E}$ contains the employee-based opportunity variables, $\boldsymbol{WE}$ contains the spatially lagged opportunity variables, and ν is gamma distributed to capture overdispersion. We first estimated models with just our control variables. We then added our GSV measures to the subsequent models, along with quadratic versions of them to capture nonlinearities (when statistically significant) and compared the pseudo R-squares as an approximate assessment of how much our GSV-based built environment variables help explain the location of crime incidents. To account of the increased number of variables in the models with our GSV variables, we also compared the Bayesian Information Criterion (BIC) values across the models. We then estimated models that also included interactions of concentrated disadvantage and our GSV variables to test for moderating effects.

Results

Table 3 presents the results of our negative binomial regression models showing how the covariates are associated with the crime counts at the segment level. The pseudo R-squared values presented near the bottom of this table indicate that there is notable improvement in the explanatory power of the models with the inclusion of GSV variables. Specifically, we find: a 19% increase in the pseudo R-squared (from 0.129 to 0.154) for the aggravated assault model, an increase of 21% for the motor vehicle theft model, a 30 and 34% increase for the burglary and larceny models, respectively, and a 63% increase for the robbery model. Likewise, the BIC values are all smaller in the models including our GSV measures, also indicating that these models are preferred to the initial models.

<<<Table 3 about here>>>

We find that two of our measures of vibrancy (buildings and humans) generally show positive relationships with the five types of crime examined in this study. The presence of more humans in the environment is associated with higher crime levels, and buildings exhibit a slowing positive relationship with these crime types as seen in Figure 2, in which we plot the relationship pattern for the 5^{th}–95^{th} percentile of the buildings measure. For a street segment with no buildings, a one standard deviation increase results in 18-38% more crime, depending on the crime type, whereas a similar increase for a street segment that was at the mean in buildings results in 12-28% more crime due to the slowing positive relationship. Our third measure of vibrancy—sidewalks—are positively associated with robberies and larcenies, and have a slowing positive relationship with burglary.

<<<Figure 2 about here>>>

Regarding the auto-oriented measures, we find that there is generally a slowing positive relationship between the presence of vehicles and crime (similar to Figure 2). A one standard deviation increase in vehicles from 0 to 2.5% is associated with 71% more motor vehicle thefts, whereas a similar increase from 2.5% to 5% is associated with 45% more motor vehicle thefts. Similar increases are associated with 28% and 20%, respectively, increases in burglaries. Pavement generally shows strong linear positive relationships with crime as a one standard deviation increase in pavement results in nearly double the robberies, and nearly 50% more of the other crime types.

The two defensible space measures of fences and walls exhibit different effects. The presence of walls has a consistent slowing negative relationship with all crime types (not shown). A one standard deviation increase in walls (0.7%) is associated with 30% fewer robberies and about 20% fewer crimes of the other types. However, the presence of fences had mixed results across the different crime types: the negative relationships with robberies and larcenies were weaker than walls with approximate 10% decreases, and fences actually had a positive relationship with aggravated assaults and a very small positive one with burglaries. Unlike walls, fences allow visibility, and the distinct effects of these two defensible space measures can be attributed to that difference.

The two greenspace measures also show differing patterns. The presence of vegetation exhibited mixed results. There was a positive relationship between vegetation and larcenies, and an inverted-U relationship with aggravated assaults. On the other hand, vegetation showed a U-shaped relationship with burglaries and robberies (not shown). Thus, whereas the highest number of aggravated assaults occurs on street segments with a moderate amount of vegetation (about 25%), these are the street segments with the fewest burglaries and robberies. In contrast, terrain that captured open green space generally had a negative relationship with crime. A one standard deviation increase in terrain is associated with 5% fewer motor vehicle thefts and 11% fewer aggravated assaults. And there are slowing negative relationships between terrain and robberies and larcenies, and a U-shaped relationship with burglaries (not shown). The presence of objects in the environment and crime generally exhibited either inverted-U or slowing positive relationships with the crime types (not shown).

Moderating effects of concentrated disadvantage

For our final set of analyses, we tested whether the level of concentrated disadvantage in the area surrounding a street segment moderated the relationship between these built environment features and levels of crime (the interaction coefficients are presented in Table 4). The general pattern for vibrancy was a negative interaction between concentrated disadvantage in the neighborhood and the vibrancy measures. For example, the presence of buildings has a stronger positive relationship with robbery and motor vehicle theft in low disadvantage neighborhoods, as seen in Figure 3. In each of the figures in this section we plot the relationship between a measure and crime when concentrated disadvantage is set to a low value (one standard deviation below the mean), an average value (the mean) and a high value (one standard deviation above the mean). On street segments with few buildings (the left side of the figures) there are more robberies (Figure 3a) and motor vehicle thefts (Figure 3b) in high disadvantage neighborhoods compared to low disadvantage ones. However, when there are many buildings, the gap between such neighborhoods narrows (the right side of the graphs). There was also a stronger positive relationship between the presence of humans and both robbery and motor vehicle theft in low disadvantage neighborhoods (not shown). Sidewalks had fewer interaction effects, although the positive relationship with burglary was stronger in low disadvantage neighborhoods. There was only one exception to this general pattern: the positive relationship for buildings and burglaries is attenuated in low disadvantage neighborhoods (Figure 3c).

<<<Table 4 about here>>>

<<<Figure 3 about here>>>

There were weaker moderating effects for the auto-related measures. The only significant interaction effects for pavement were quite modest when plotted. Only the relationships between vehicles and the three property crimes were stronger in low disadvantage neighborhoods. We plot this effect for burglaries in Figure 4a, and we see on the left side of the graph that with few vehicles, there are modestly more burglaries in high disadvantage neighborhoods compared to low disadvantage ones. However, as the number of vehicles increases, burglaries are more frequent in *low disadvantage* neighborhoods (the right side of this figure). At high levels of vehicles, there are about 30% more burglaries in a low disadvantage versus a high disadvantage neighborhood. For motor vehicle thefts, the gap between high and low disadvantage neighborhoods narrows when there are more vehicles present (Figure 4b), and completely evaporates for larcenies (Figure 4c).

<<<Figure 4 about here>>>

It is interesting to note that the moderating effects of concentrated disadvantage for the two defensible space measures of walls and fences operated differently. On the one hand, fences have a stronger negative relationship with violent crimes in low disadvantage neighborhoods. Robbery is particularly strongly lower at locations with many fences and low concentrated disadvantage, whereas in high disadvantage neighborhoods the presence of fences only results in modestly fewer robberies (Figure 5a). In contrast, walls have a stronger negative relationship with crime in high disadvantage neighborhoods, and this effect is particularly strong for robbery and burglary. On street segments with many walls there is little difference in the number of robberies depending on the level of disadvantage, whereas segments with few walls have 52% more robberies if they are in a high disadvantage rather than low disadvantage neighborhood (Figure 5c). And for two street segments with a high presence of walls, we find that the burglary rates are the same regardless the level of disadvantage, which also highlights how walls may be more effective in these disadvantaged locations (Figure 5d).

<<<Figure 5 about here>>>

Finally, there is very little evidence that the level of concentrated disadvantage in the neighborhood moderates the relationship between greenspace and crime. The control variables generally have the expected relationships with crime levels. Among others, longer street segments and those with more population, consumer employees or non-consumer employees have higher crime levels. Higher levels of vacant units in the surrounding area are associated with higher levels of crime. In contrast, residential stability in nearby areas is found to be negatively associated with property crime.

Conclusion

This study built on recent research and demonstrated how extracting features of the built environment from GSV images with a machine learning technique is useful for exploring how these features are related to crime at the micro scale (Weisburd, Groff, and Yang 2012). While one prior study used this strategy on a mid-sized city (Hipp et al. 2021), we used the technique on the very large city of Los Angeles and found generally similar effects. An advantage of semantic segmentation is extracting visible cityscape elements from the pedestrian perspective, and these are features that are typically difficult to measure. Our results showed that these measures of fences, walls, buildings, greenspace, etc., considerably improve the fit of our models, highlighting their importance. These measures particularly strongly improved the model performance explaining the locations of robberies, similar to an earlier study of a mid-sized city (Hipp et al. 2021). An important contribution to the current study was then demonstrating how the level of concentrated disadvantage in the area surrounding these street segments moderates the relationship between these built environment measures and crime levels.

It is notable that, similar to a prior study on the mid-sized city of Santa Ana, the environmental measures attempting to capture vibrancy were actually associated with *higher* levels of crime. The measure of buildings in the environment is meant to capture those close to the street that can influence the behavior of individuals in the environment, as are often found in walkable downtown locations. Whereas this measure of buildings was generally insignificantly related to crime levels in the city of Santa Ana, it was actually associated with more crime in our study area of Los Angeles. We highlight that we controlled for the number of consumer-facing or non-consumer business employees in the segment, so our building measure is capturing the built environment specifically. Our measure of people in the environment captures areas with more people walking about, which we presumed would capture vibrancy, but it may simply be an indicator of more crime opportunities rather than the presence of more potential guardians. This is consistent with prior research finding that a larger ambient population is associated with more crime on street segments (Hipp et al. 2019; Malleson and Andresen 2015). Furthermore, our measures of buildings and people in the environment had particularly strong positive relationships with robbery and motor vehicle theft in low disadvantage neighborhoods, which may be consistent with a saturation pattern in which the presence of more opportunities in the environment does not increase crime any further in high disadvantage neighborhoods, and instead is most salient in low disadvantage locations that otherwise had lower crime levels.

We found that street segments with more of our auto-oriented measures tended to have more crime. Consistent with a study of the city of Santa Ana (Hipp et al. 2021), the presence of more vehicles or more pavement in the environment were associated with more crime, and our presumption is that these measures—particularly in combination—are often capturing parking lots fronting the street. Such environments are less walkable, and thus are expected to have fewer guardians. Our results were consistent with this expectation, and were even stronger in low disadvantage neighborhoods for burglaries and larcenies. This is also in line with the idea of a saturation effect in high disadvantage neighborhoods in which such increased opportunities simply do not further increase crime.

Another notable finding is that fences and walls had different relationships with crime, and these patterns even differed across high and low disadvantage neighborhoods. Consistent with an earlier study of Santa Ana, walls exhibit a much stronger negative relationship with crime than do fences. This pattern was very pronounced in our study and highlights that this appears to be a robust pattern. This is notable as one might presume based on the insights of CPTED that walls would not be as beneficial as fences since they also obstruct views, which would allow potential offenders to be out of sight of potential guardians. However, this clearly was not the case in our study site, so more careful thought is needed about how walls serve a beneficial purpose. It may be that the height of the barrier is what is particularly important, although we were not able to assess this here. Furthermore, walls were particularly beneficial for preventing robbery and burglary in high disadvantage neighborhoods. For burglaries, if high disadvantage neighborhoods have less informal social control, as found in earlier studies (Hipp and Wickes 2017; Peterson and Krivo 2009; Sampson and Groves 1989), walls may be particularly beneficial as the reduced visibility is not impacting much potential guardianship. Fences had a much weaker negative relationship with crime—only exhibiting negative relationships with robberies and larcenies—and actually were associated with more burglaries and aggravated assaults. Fences simply were not as effective as walls at reducing crime. Furthermore, a distinction is that fences only exhibited a negative relationship with violent crime when they were located in low disadvantage neighborhoods. If fences operate as more symbolic boundaries to create a sense of ownership of a space and increase potential guardianship, this may be most effective in neighborhoods that already have more potential informal social control. This further highlights the distinction with walls, which were particularly beneficial in high disadvantage neighborhoods.

It is interesting to note that the results for greenspace measures were considerably different from research in the mid-sized city of Santa Ana. Whereas in that study terrain generally exhibited a positive relationship with crime, in our study of Los Angeles terrain generally exhibited a *negative* relationship with crime. Only for burglary was there a U-shaped relationship, indicating that there are more burglaries in locations with the highest concentration of terrain. For vegetation, we detected the expected positive relationship between this measure and burglaries, as CPTED would expect that such shrubbery can serve as camouflage for offenders near a unit. Likewise, vegetation had a U-shaped relationship with robberies, which could also indicate that high levels of such vegetation can serve to minimize guardianship capability. One similarity with a study of Santa Ana was the robust inverted U-shaped relationship with aggravated assaults, indicating that a moderate amount of vegetation is particularly crime enhancing for aggravated assaults. We do not have a hypothesis for why this would occur, but the robustness of this finding across two different study sites suggests that it is something that needs more theoretical consideration.

Some limitations of this study deserve mention. First, although we had some expectations for the direction of the relationships between certain features and some types of crime, other feature results were not hypothesized and highlight the novelty of the strategy. Second, we did not measure mechanisms, and therefore we do not know why exactly we observed particular relationships. Third, although GSV is a powerful tool, a limitation is that we have no control over the time of day or the season that images were taken. This is arguably most impactful for the ephemeral measures of humans or vehicles. As well, there are temporal issues given that some images are from 2019 and 2020 and the crime data is for 2017-19; however, the built environment arguably changes very little so we do not believe this introduces much bias.

In conclusion, this study has built on recent research demonstrating the usefulness of measuring the built environment with elements extracted from GSV images using a machine learning technique. The results showed that the built environment has important consequences for crime levels of street segments in the large city of Los Angeles, in several instances showing similar results to an earlier study of a mid-sized city (Hipp et. al. 2021). Nonetheless, some results pose a challenge for theories such as CPTED, as walls consistently had a much stronger negative relationship with crime compared to fences (which allow more visibility). Furthermore, there were important differences in how some of these built environment measures operated across low and high disadvantage neighborhoods, as we generally found stronger effects in *low* disadvantage neighborhoods. These results highlight the importance of future research and policy dialogue taking more seriously the social context in which such built environment features exist.

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Tables and Figures

Table 1. Summary statistics of variables used in analyses

	Mean	S.D.
Dependent variables		
Aggravated assaults	0.85	2.49
Robberies	0.24	1.17
Burglaries	0.61	1.59
Motor vehicle thefts	0.57	1.54
Larcenies	2.30	9.79
Street view characteristics		
Percent buildings	5.4	5.2
Percent humans	0.1	0.1
Percent sidewalks	3.1	1.4
Percent vehicles	3.4	2.4
Percent pavement	19.0	3.8
Percent fences	1.2	1.3
Percent walls	0.5	0.7
Percent vegetation	21.8	13.3
Percent terrain	2.1	1.9
Percent objects	0.7	0.5
Percent sky	42.7	0.0
Demographic variables: 1/2 mile exponential decay		
Percent Asian	10.5	9.1
Percent Black	8.5	13.5
Percent Latino	41.9	28.0
Racial/ethnic heterogeneity	0.5	0.2
Concentrated disadvantage	-1.7	11.9
Percent vacant units	6.2	3.2
Residential stability	0.0	0.9
Percent aged 16 to 29	22.2	6.8
Segment variables		
Segment length (logged)	5.0	0.6
Population (logged)	4.7	1.4
Residential segment	0.68	0.47
Number of non-consumer employees	18.2	132.8
Number of consumer-facing employees	2.7	38.9
Surrounding 1/2 mile inverse distance decay		
Population (logged)	8.7	0.8
Number of non-consumer employees (in 1000s)	9.2	21.6
Number of consumer-facing employees (in 1000s)	2.7	4.6
N = 66,844 street segments in Los Angeles		

Table 2. Correlations of independent variables in models

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	Vehicles																								
2	Pavement	-0.19																							
3	Vegetation	-0.24	-0.37																						
4	Terrain	-0.26	-0.19	0.19																					
5	Buildings	0.28	-0.04	-0.34	-0.29																				
6	Humans	0.19	0.07	-0.24	-0.21	0.28																			
7	Sidewalks	-0.21	-0.12	-0.15	-0.08	0.09	0.03																		
8	Objects	0.14	0.26	-0.48	-0.32	0.18	0.28	0.09																	
9	Fences	0.11	-0.22	-0.19	-0.23	0.05	0.07	0.12	0.19																
10	Walls	-0.03	-0.17	0.02	-0.11	0.00	-0.02	0.07	0.02	0.17															
	Segment variables																								
11	Non-consumer employees	0.04	0.09	-0.07	-0.08	0.17	0.08	0.00	0.07	-0.03	-0.02														
12	Consumer-facing employees	0.03	0.05	-0.05	-0.05	0.06	0.05	0.00	0.05	-0.01	-0.02	0.11													
13	Length of segment (logged)	0.03	-0.06	0.09	0.07	-0.09	-0.03	-0.04	-0.15	0.01	-0.08	0.10	0.05												
14	Population (logged)	0.00	-0.18	0.15	0.04	-0.13	-0.13	-0.03	-0.20	0.00	-0.03	-0.11	-0.04	0.06											
	Exponential decay																								
15	Percent Asian	-0.06	0.07	0.01	0.04	0.11	-0.02	0.08	-0.06	-0.16	-0.02	0.06	0.01	0.00	-0.01										
16	Percent Black	0.08	0.03	-0.23	0.08	0.09	0.13	-0.05	0.13	0.09	-0.08	-0.01	0.00	0.01	-0.06	-0.29									
17	Percent Latino	0.27	0.10	-0.39	-0.18	0.02	0.13	0.02	0.32	0.38	0.06	-0.02	0.00	-0.04	0.04	-0.23	0.03								
18	Racial/ethnic heterogeneity	-0.06	0.07	-0.04	0.15	0.06	-0.02	0.05	-0.07	-0.18	-0.05	0.04	0.02	0.00	-0.05	0.56	0.09	-0.32							
19	Concentrated disadvantage	0.30	0.15	-0.49	-0.15	0.15	0.21	0.04	0.37	0.36	0.01	0.01	0.01	-0.04	-0.02	-0.11	0.32	0.80	0.02						
20	Percent vacant units	0.18	-0.02	-0.10	-0.20	0.34	0.21	-0.07	0.16	0.10	0.00	0.09	0.04	-0.02	-0.16	-0.06	0.16	-0.03	0.01	0.10					
21	Residential stability	-0.36	-0.06	0.31	0.27	-0.40	-0.25	0.03	-0.33	-0.19	0.02	-0.09	-0.04	0.03	0.09	-0.10	-0.09	-0.30	-0.16	-0.56	-0.46				
22	Percent aged 16 to 29	0.25	0.12	-0.32	-0.14	0.20	0.15	0.02	0.24	0.20	-0.02	0.04	0.02	-0.03	-0.02	0.10	0.09	0.46	0.12	0.59	0.15	-0.57			
	Surrounding 1/2 mile																								
23	Population (logged)	0.31	-0.01	-0.28	-0.09	0.23	0.13	0.02	0.19	0.17	-0.04	0.00	0.00	-0.08	0.24	0.04	0.17	0.44	0.06	0.55	0.05	-0.53	0.48		
24	Non-consumer employees	0.15	0.09	-0.13	-0.14	0.45	0.23	0.03	0.09	-0.03	-0.04	0.25	0.06	0.00	-0.16	0.25	0.00	-0.07	0.15	0.07	0.30	-0.33	0.24	0.15	
25	Consumer-facing employees	0.20	0.06	-0.16	-0.18	0.52	0.31	0.02	0.15	-0.02	-0.05	0.19	0.11	-0.02	-0.18	0.17	0.03	-0.08	0.14	0.09	0.37	-0.42	0.21	0.20	0.69

N = 66,844 street segments in Los Angeles

Table 3. Negative binomial regression models predicting crime in street segments using built environment GSV measures

	Aggravated assault		Robbery		Burglary		Motor vehicle theft		Larceny	
Street view characteristics										
Buildings	0.0735	**	0.0386	**	0.0582	**	0.0472	**	0.0761	**
	(18.22)		(6.19)		(14.91)		(11.95)		(25.45)	
Buildings squared	-0.0014	**	-0.0009	**	-0.0014	**	-0.0009	**	-0.0018	**
	-(12.81)		-(5.56)		-(12.64)		-(8.13)		-(22.40)	
Humans	1.354	**	2.222	**	0.527	**	-0.063		1.125	**
	(12.11)		(15.05)		(6.09)		-(1.00)		(15.90)	
Humans squared	-0.397	**	-0.499	**	-0.078	**			-0.186	**
	-(6.14)		-(7.66)		-(4.20)				-(13.38)	
Sidewalks	-0.0998	**	0.0262	*	0.0462	**	-0.0439	*	0.0305	**
	-(4.92)		(2.12)		(6.85)		-(2.22)		(5.82)	
Sidewalks squared	0.0142	**					0.0058	*		
	(5.43)						(2.23)			
Vehicles	0.1141	**	0.1154	**	0.1089	**	0.2490	**	0.1267	**
	(19.16)		(8.43)		(12.00)		(21.36)		(21.46)	
Vehicles squared	-0.0010	**	-0.0025	**	-0.0046	**	-0.0135	**	-0.0038	**
	-(6.10)		-(3.08)		-(6.20)		-(12.53)		-(9.58)	
Pavement	0.1584	**	0.2699	**	0.1364	**	0.1480	**	0.1252	**
	(11.34)		(10.43)		(10.61)		(11.34)		(12.60)	
Pavement squared	-0.0019	**	-0.0035	**	-0.0017	**	-0.0019	**	-0.0011	**
	-(5.95)		-(6.44)		-(5.94)		-(6.54)		-(4.76)	

Fences	0.0805 **	-0.1273 **	0.0079 **	-0.0016	-0.1187 **
	(5.34)	-(5.44)	(3.45)	-(0.21)	-(10.73)
Fences squared	-0.0077 **	0.0125 **			0.0097 **
	-(3.32)	(3.58)			(5.79)
Walls	-0.3175 **	-0.5271 **	-0.3396 **	-0.2834 **	-0.3532 **
	-(14.72)	-(13.80)	-(16.43)	-(13.76)	-(22.19)
Walls squared	0.0202 **	0.0392 **	0.0218 **	0.0159 **	0.0205 **
	(5.95)	(7.18)	(6.37)	(4.65)	(7.37)
Vegetation	0.0091 **	-0.0146 **	-0.0060 **	0.0006	0.0007
	(3.63)	-(3.64)	-(2.68)	(0.67)	(0.37)
Vegetation squared	-0.0002 **	0.0003 **	0.0001 **		0.0000
	-(3.53)	(3.53)	(3.77)		(1.16)
Terrain	-0.0630 **	-0.1600 **	-0.0413 **	-0.0264 **	-0.0784 **
	-(5.03)	-(7.83)	-(3.64)	-(4.41)	-(8.69)
Terrain squared		0.0124 **	0.0069 **		0.0076 **
		(4.77)	(4.95)		(6.72)
Objects	0.2644 **	0.7514 **	0.2024 **	0.3840 **	0.2336 **
	(6.00)	(11.17)	(10.79)	(8.79)	(15.89)
Objects squared	-0.0389 *	-0.0817 **	-0.0958 **	-0.0667 **	
	-(2.46)	-(3.81)	-(6.57)	-(4.13)	
Segment variables					
Length of segment (logged)	1.204 **	1.152 **	1.196 **	1.188 **	1.192 **
	(82.40)	(46.86)	(86.26)	(86.81)	(110.04)
Population (logged) in segment	0.2829 **	0.1383 **	0.0887 **	0.1602 **	0.1551 **
	(41.88)	(13.94)	(14.28)	(26.18)	(32.56)

Residential segment	-0.1285	**		-0.5469	**		-0.2345	**		-0.0992	**	-0.2308	**
	-(6.51)			-(16.92)			-(12.12)			-(5.36)		-(15.02)	
Number of non-consumer employees	0.0003	**		0.0001	†		0.0003	**		0.0002	**	0.0005	**
	(5.56)			(1.75)			(5.16)			(4.36)		(7.97)	
Number of consumer-facing employees	0.0007	**		0.0058	**		0.0012	**		0.0015	**	0.0058	**
	(3.73)			(11.97)			(5.35)			(7.90)		(19.09)	
Demographic variables: exponential decay													
Percent Asian	-0.0081	**		-0.0063	**		-0.0017	†		0.0011		-0.0045	**
	-(7.21)			-(3.65)			-(1.66)			(1.10)		-(5.34)	
Percent Black	0.0133	**		0.0140	**		0.0048	**		0.0099	**	0.0015	**
	(16.69)			(10.45)			(6.60)			(13.11)		(2.62)	
Percent Latino	0.0063	**		-0.0014			-0.0076	**		0.0111	**	-0.0024	**
	(7.96)			-(1.00)			-(11.22)			(15.17)		-(4.44)	
Racial/ethnic heterogeneity	0.3551	**		0.2657	*		-0.0968			0.4486	**	0.5147	**
	(4.90)			(2.23)			-(1.41)			(6.68)		(9.53)	
Concentrated disadvantage	0.0301	**		0.0272	**		0.0002			0.0092	**	0.0119	**
	(13.08)			(6.78)			(0.11)			(4.46)		(8.04)	
Percent vacant units	0.0267	**		0.0416	**		0.0212	**		0.0220	**	0.0074	**
	(8.15)			(8.16)			(7.26)			(7.56)		(2.91)	
Residential stability	-0.0829	**		0.0327			-0.0359	*		-0.1394	**	-0.1658	**
	-(4.77)			(1.08)			-(2.27)			-(8.72)		-(13.66)	
Percent aged 16 to 29	-0.0038	*		0.0041	†		-0.0026	†		-0.0048	**	0.0018	
	-(2.32)			(1.72)			-(1.80)			-(3.06)		(1.56)	

Surrounding 1/2 mile														
Number of non-consumer employees	-0.0012	*		-0.0016	*		-0.0022	**		-0.0022	**		-0.0012	**
	-(2.45)			-(2.43)			-(4.61)			-(4.40)			-(3.42)	
Number of consumer-facing employees	0.0182	**		0.0152	**		0.0111	**		0.0052	*		0.0308	**
	(7.51)			(4.24)			(4.85)			(2.30)			(15.70)	
Population (logged)	0.1566	**		0.4843	**		0.2559	**		0.0577	**		-0.0097	
	(10.49)			(17.31)			(17.35)			(4.32)			-(1.18)	
Intercept	-13.21	**		-17.64	**		-11.56	**		-11.96	**		-9.15	**
	-(51.07)			-(36.35)			-(48.85)			-(50.21)			-(53.75)	
Pseudo R-square	0.155			0.188			0.100			0.145			0.126	
Pseudo R-square (without GSV variables)	0.134			0.141			0.083			0.124			0.101	
Percent increase in pseudo R-square	15.7%			33.3%			20.5%			16.9%			24.8%	
BIC	126,818			55,983			123,703			112,420			215,693	
BIC (without GSV variables)	129,678			58,949			125,845			115,099			221,593	

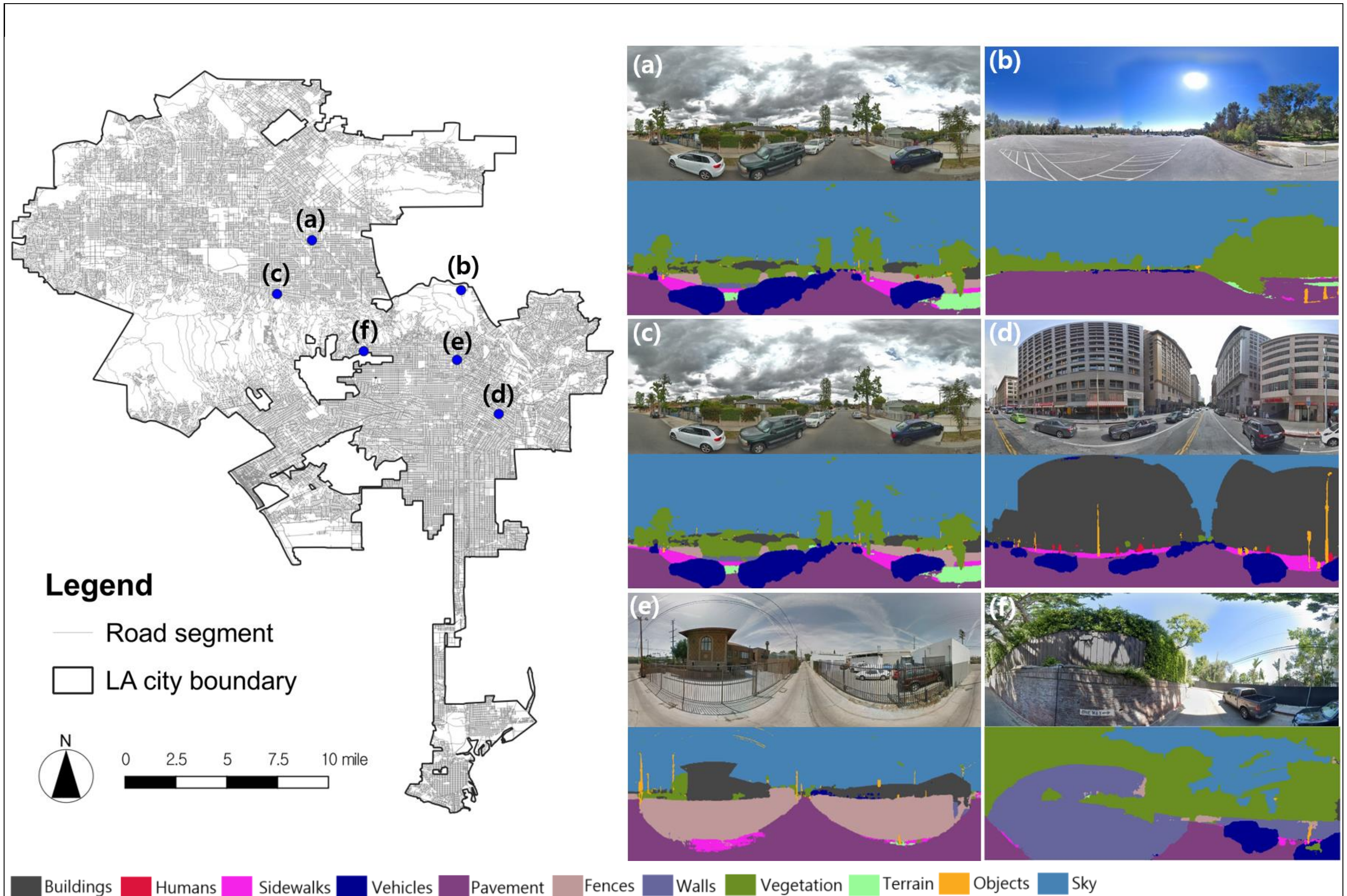
*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .10 (two-tail test). T-values in parentheses. N=66,844 street segments.*

Table 4. Negative binomial regression models predicting crime in street segments, including interactions between built environment GSV measures and concentrated disadvantage

	Aggravated assault		Robbery		Burglary		Motor vehicle theft		Larceny	
Interaction variables between GSV measure and concentrated disadvantage										
Percent vehicles	-0.001	*	-0.0008		-0.0025	**	-0.0034	**	-0.0021	**
	-2.04		-0.91		-6.05		-7.36		-6.62	
Percent pavement	-0.001	**	-0.0002		-0.0002		-0.0008	*	0.0005	*
	-2.83		-0.38		-0.73		-2.52		2.07	
Percent vegetation	-0.0002	*	-0.0002		0.0001	†	-0.0002	†	0	
	-2.26		-0.88		1.75		-1.87		0.43	
Percent terrain	0.0004		-0.0013		-0.001	*	-0.0013	*	-0.0011	**
	0.68		-1.19		-2.24		-2.32		-3.06	
Percent buildings	-0.0008	**	-0.001	**	0.0008	**	-0.0012	**	-0.0007	**
	-3.9		-3.06		4.3		-6.42		-5.33	
Percent humans	-0.0193	*	-0.0363	**	-0.0129		-0.0247	**	-0.0175	**
	-2.25		-2.8		-1.64		-2.88		-2.67	
Percent sidewalks	0.0003		0.0017		-0.0025	**	-0.0011		-0.0004	
	0.37		1.38		-4.47		-1.62		-0.94	
Percent objects	-0.0149	**	-0.0119	**	0.0019		-0.0088	**	-0.0069	**
	-7.26		-3.88		1.09		-4.51		-4.97	
Percent fences	0.0023	*	0.0073	**	0.0004		-0.0004		0.0001	
	2.36		4.08		0.48		-0.44		0.18	
Percent walls	-0.0043	**	-0.0077	**	-0.0038	**	0.0002		-0.0044	**
	-2.85		-2.76		-3.09		0.14		-4.53	

Note: Main effects of the GSV measures and concentrated disadvantage are suppressed, as are the control variables

Figure 1. Examples of categorization of GSV images



(a)		(b)		(c)		(d)		(e)		(f)	
Sky	55.24	Sky	47.00	**Vegetation**	**46.94**	**Building**	**54.27**	Sky	39.88	Vegetation	41.42
Pavement	13.28	**Pavement**	**30.42**	Sky	21.19	Pavement	19.30	Pavement	22.95	**Wall**	**29.11**
Vegetation	12.72	Vegetation	21.13	Pavement	14.18	Sky	15.40	**Fence**	**20.91**	Sky	14.82
Vehicle	**9.00**	Terrain	0.49	Sidewalk	5.65	Vehicle	7.11	Building	9.69	Road	8.61

Building	2.52	Vehicle	0.38	Terrain	3.76	Sidewalk	2.32	Sidewalk	3.29	Vehicle	4.55

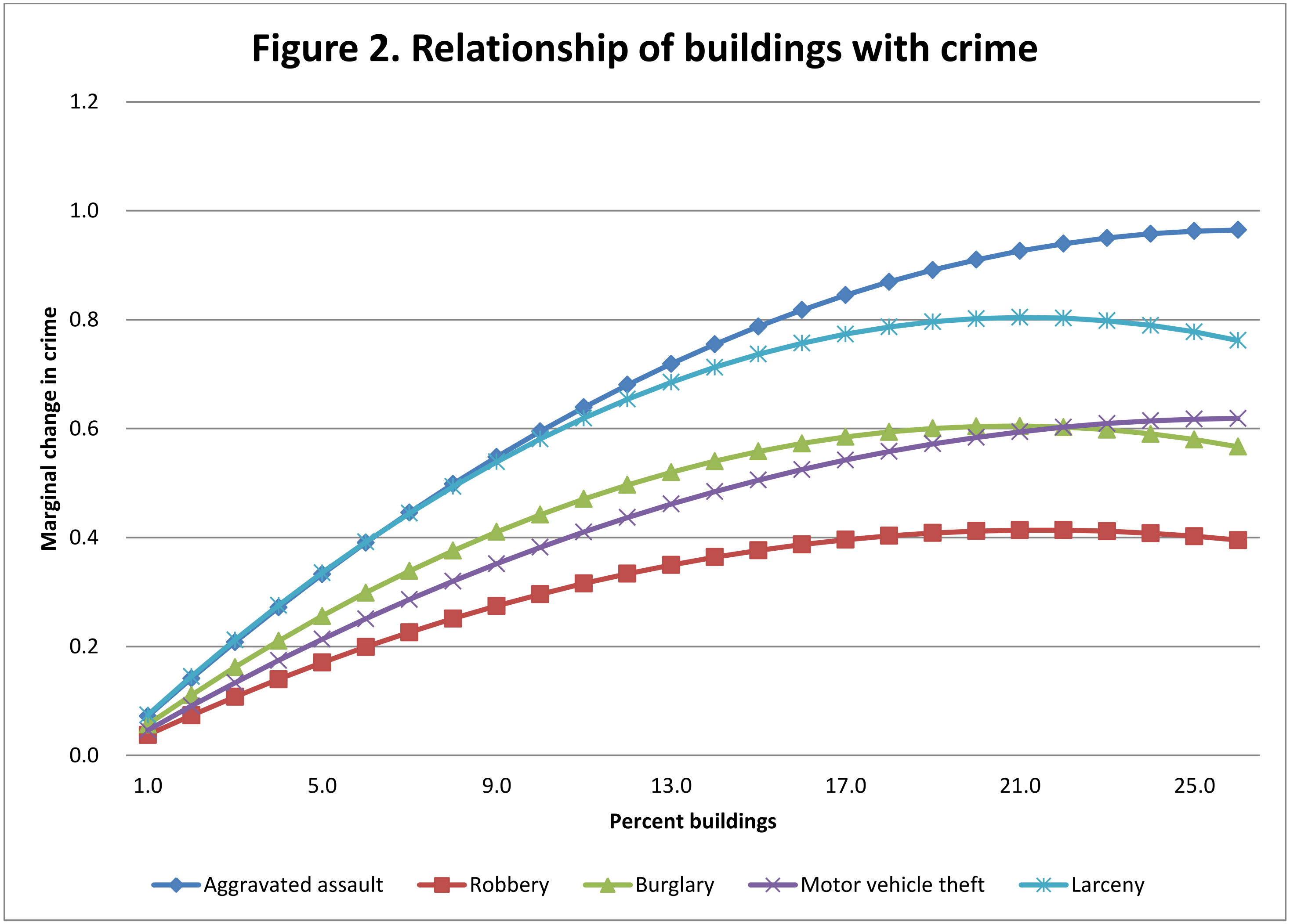


Figure 3a. Buildings and disadvantage for robbery

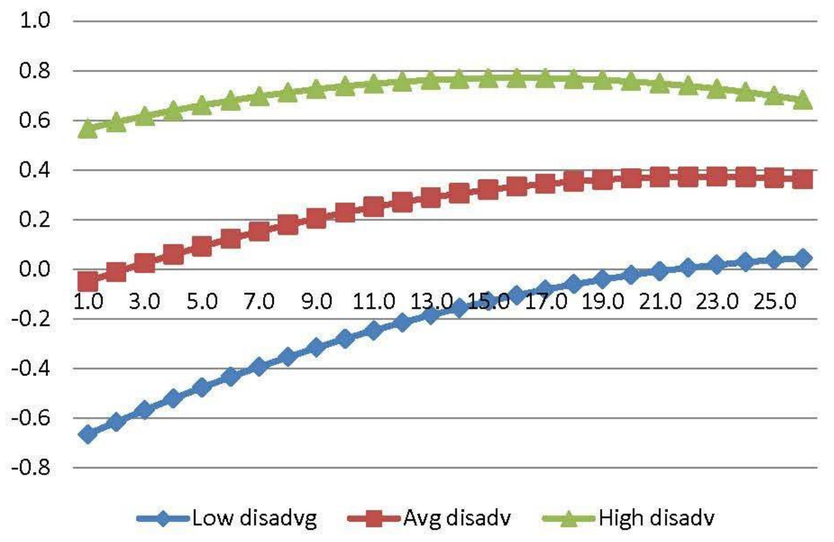


Figure 3b. Buildings and disadvantage for MV theft

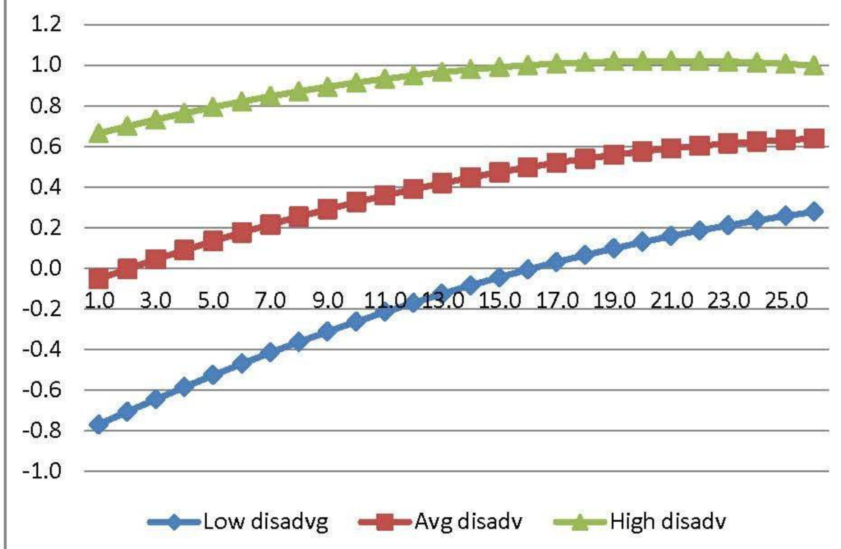


Figure 3c. Buildings and disadvantage for burglary

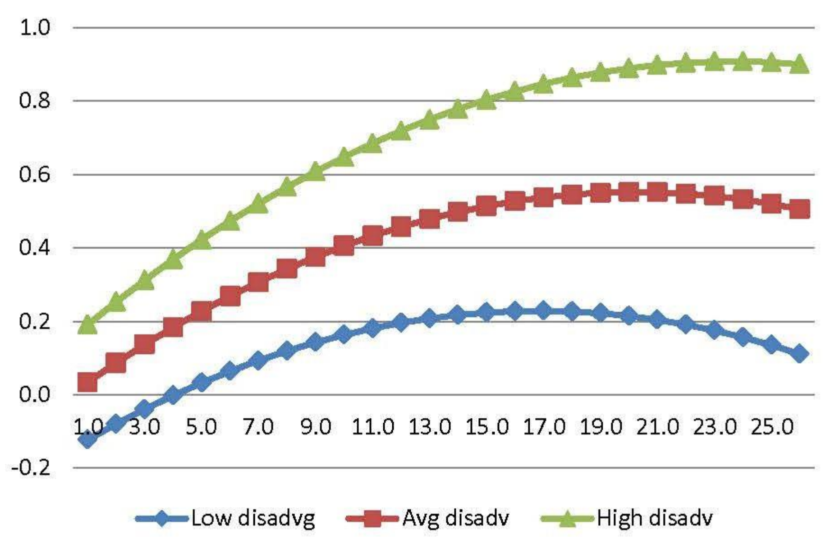


Figure 4a. Vehicles and disadvantage for burglary

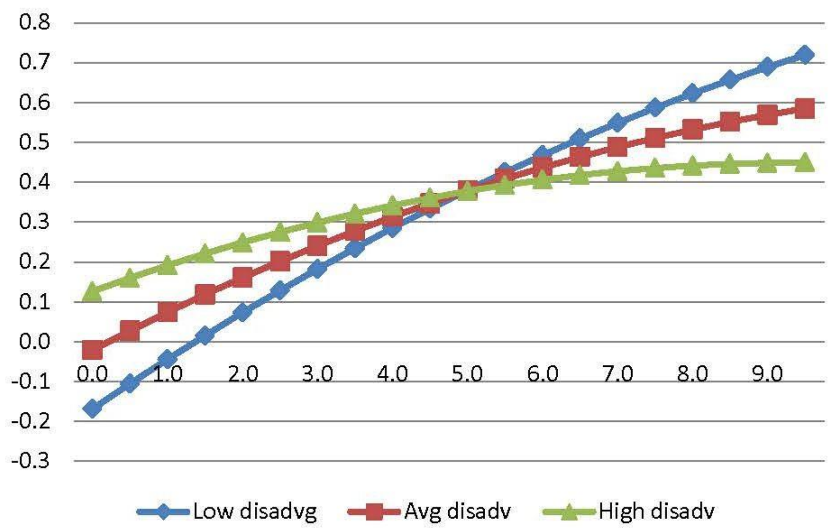


Figure 4b. Vehicles and disadvantage for MV theft

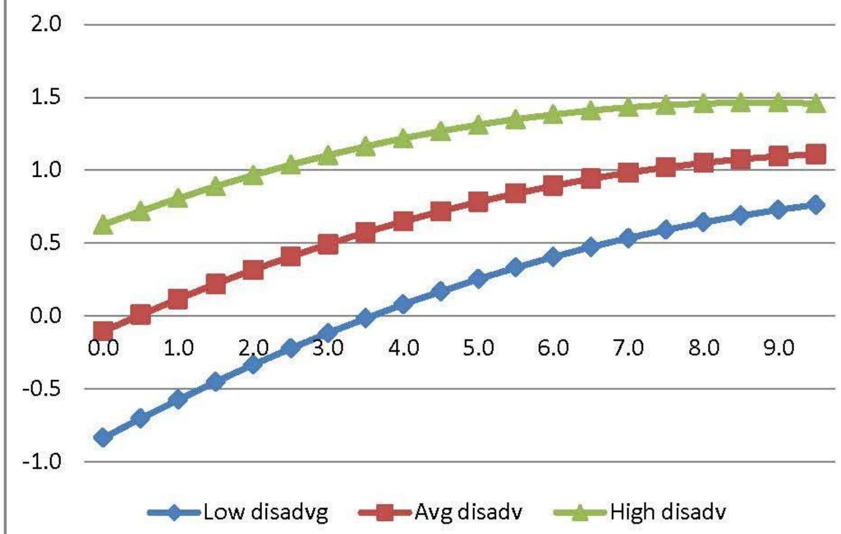


Figure 4c. Vehicles and disadvantage for larceny

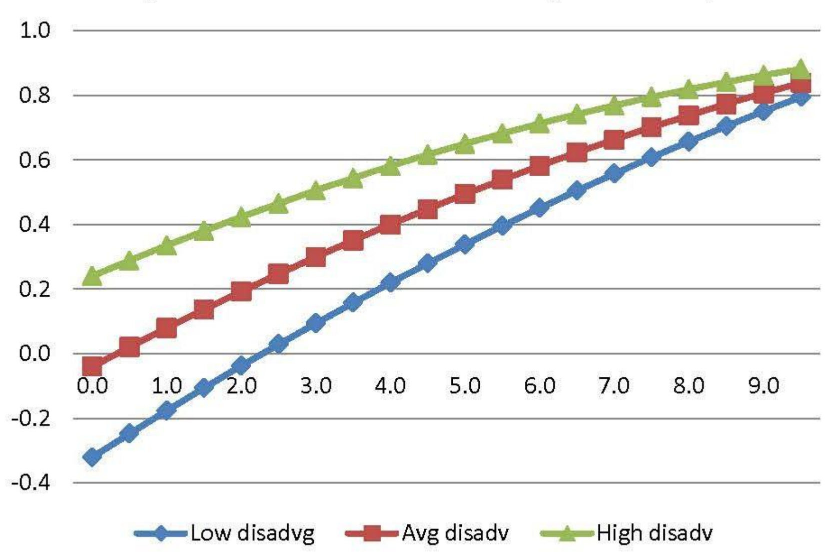


Figure 5a. Fences and disadvantage for robbery

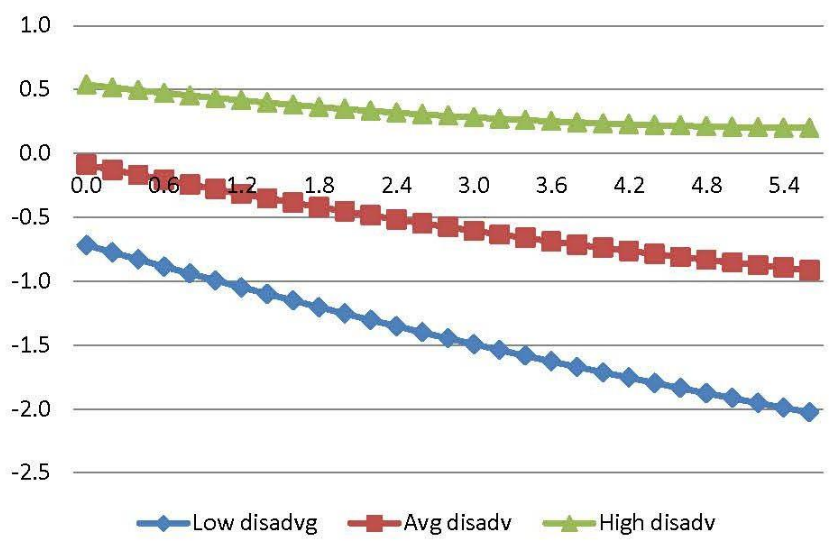


Figure 5b. Fences and disadvantage for aggravated assault

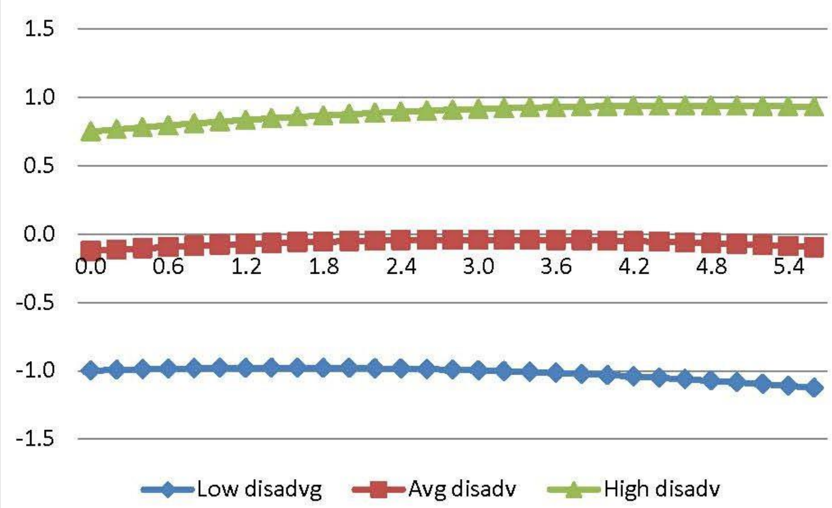


Figure 5c. Walls and disadvantage for robbery

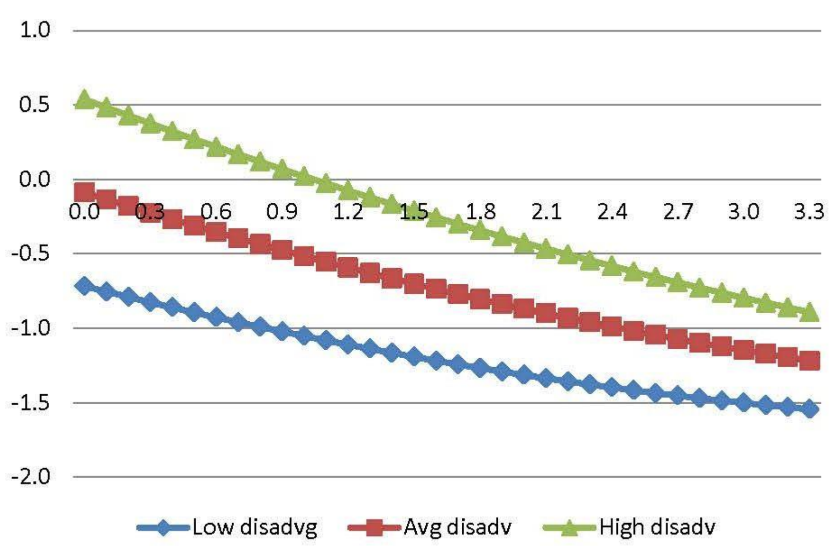


Figure 5d. Walls and disadvantage for burglary