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Business environment ecology and crime: A robust test across 182 cities

Abstract

Studies assessing the question of how certain types of business establishments are related to the level of crime on blocks typically do not account for the general business context of those blocks. The present study extends one previous study that did so by using a large sample of blocks across 182 cities in the U.S. We assess whether measuring the general business context of blocks as three broad categories of businesses—consumer-facing businesses, blue-collar businesses, and white-collar businesses—along with the heterogeneity of consumer businesses on a block can explain where crime occurs. The study finds that these four measures explain much of the variation in crime due to businesses across blocks. Furthermore, whereas 12 specific types of businesses exhibit strong relationships with crime when not accounting for this business context, their relationships with crime greatly diminish, or completely evaporate, once accounting for the general business context. Finally, blocks with more consumer business heterogeneity have higher levels of crime, and this relationship is stronger in small population cities and in low population areas.

Keywords: business environment, micro crime locations

Bio

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

Cheyenne Hodgen is a Ph.D. student in the department of Criminology, Law and Society, at the University of California, Irvine. Her research interests include spatio-temporal patterns of crime and the relationship between the built environment and crime.

Business environment ecology and crime: A robust test across 182 cities

There is consistent evidence in the criminological literature that the presence of certain types of businesses on street blocks is associated with the location of crime across cities. Criminological theory posits that some businesses provide crime opportunities and therefore certain types of crime are more likely to occur at these locations (Brantingham and Brantingham 1993; Felson 2002). A common strategy in the literature is to measure specific types of businesses and assess whether blocks with such businesses are likely to experience more crime incidents. Despite the useful insights this strategy has provided, a recent study highlighted the importance of also accounting for the broader business context on the particular street block where the business is located (Hipp and Hodgen 2024). This same study of blocks in Southern California demonstrated that the general business context of a street segment appears to capture most of the crime opportunities, and that failing to account for this general business context resulted in biased estimates of the amount of crime on blocks attributable to specific types of businesses.

Although this previous study provided key insights of the importance of accounting for the general business context on blocks, a limitation is that it focused only on blocks in a single metropolitan area—the Southern California region (Hipp and Hodgen 2024). This leaves unanswered the question of whether these results are robust to other city contexts. Given the large number of studies that have assessed the relationship between specific types of businesses and crime—for example, bars or liquor stores—it is important to know whether the results of those extant studies are robust when accounting for the business context of blocks. It is possible that there is simply something unique about the Southern California region, and that in cities in older established areas of the country, including the northeast and Midwest, this business context will not have such a pronounced impact on the location of crime across blocks. We assess the robustness of these earlier results here using a sample of 182 cities with a population of at least 50,000 from across the United States that vary based on many characteristics.

Furthermore, our study also contains three additional innovations. First, whereas the earlier study of the Southern California region used measures of specific businesses that were relatively broad in nature, we use measures of 12 specific business types that have the strongest positive relationships with crime when not accounting for the business context of blocks. We then test the robustness of these 12 specific business types when accounting for the general business context of the block. Second, we assess whether the business environment of the surrounding blocks has a further impact on where crime occurs. That is, not only may the business environment of the local block impact the amount of crime near a business location, but we test whether being part of a larger business district (based on the businesses in the nearby blocks within a ½ mile buffer) has further consequences for levels of crime on the block. Third, we test whether the relationship between consumer business heterogeneity and crime is moderated by the socio-demographic context of the block, or the city socio-demographic context.

The paper takes the following course. In the next section we describe the literature discussing the potential relationship between the business context and crime on micro-units. Following that we describe the data and methods used in this study. We then present our results, and conclude with a discussion of lessons learned.

Literature Review

Theoretical reasons businesses might impact crime

Business ecology and crime

Whereas businesses have long played an important role in modern society by providing economic wealth, jobs, and goods and services to residents, the criminological literature has consistently shown that their presence is generally associated with increased crime incidents at micro-locations such as street blocks. In criminological theories, the typical explanation is that these businesses provide crime opportunities (Brantingham and Brantingham 1993; Felson 2002). Furthermore, given that specific types of businesses have functions that might attract certain types of persons, or even offenders, a body of literature has focused on whether the presence of certain types of businesses on a block is related to increased amounts of crime on the block (Roncek and Maier 1991; Gorman et al. 2001). For example, numerous studies have focused on businesses such as bars (Roncek and Maier 1991; Gorman et al. 2001), or alcohol establishments more broadly (Feng et al. 2018; Scribner et al. 1999), and tested whether the presence of these establishments on a block is related to the amount of crime. Other research has measured the presence of several types of businesses (Wilcox et al. 2004; Smith, Frazee, and Davison 2000; Bernasco and Block 2011). The limitation of this general strategy is that each block has a specific context in which a particular business is surrounded by other businesses (or the lack of such businesses). Thus, such studies cannot assure that it is the specific type of business that is attracting the crime, but simply must assume it.

A consistent limitation in much of this body of literature is failing to account for this broader business context when studying the impact of specific businesses. A recent study of businesses in the Southern California region highlighted the importance of accounting for this business context (Hipp and Hodgen 2024). This study demonstrated that the business context appeared to be adequately captured with just a few variables. Specifically, they included one measure capturing the number of consumer-facing businesses, given that they have employees but also attract customers and therefore likely provide more crime opportunities (Hipp and Luo 2022). The study then split the remaining businesses into white-collar and blue-collar businesses given that they imply very different land use features in the environment, and therefore different crime patterns (Boessen and Hipp 2015; Hipp, Kim, and Wo 2021; Kubrin and Hipp 2016). Given that these white-collar and blue-collar businesses tend to not attract customers, the smaller ambient population near them would likely not impact violent crimes as much as property crimes. Just these three measures, along with a novel measure of the degree of heterogeneity among consumer-facing businesses, appeared to capture much of the business context. Furthermore, the inclusion of these business context measures greatly reduced the size of the coefficients for the variables capturing specific types of businesses, demonstrating that failing to account for the business context can bias such measures. These considerations lead to our first three hypotheses:

H1: Accounting for the business context will greatly reduce the coefficients of specific types of businesses

H2: There will be a positive relationship between consumer-facing businesses and violent and property crime

H3: There will be a positive relationship between white-collar or blue-collar businesses and property crime

Consumer business heterogeneity and crime

Rather than simply focusing on the *number* of businesses on a block, Hipp and Hodgen (2024) argued that there are theoretical reasons why the *mix* of consumer-facing businesses (that is, the *heterogeneity* of these businesses) might impact crime levels, and they tested this in Southern California blocks and found a robust positive relationship (Hipp and Hodgen 2024).

Business ecology and crime

They noted that there are competing perspectives, as one view is that the mix of businesses on a street might increase vibrancy and therefore reduce crime due to the increased "eyes on the street" (Jacobs 1961). A counter view is that such busy streets will also have more potential targets and offenders, which could result in *more* crime (Birks and Davies 2017). Yet other possibilities are that consumer business heterogeneity impacts the mix of offenders coming to a location (van Sleeuwen, Ruiter, and Steenbeek 2021), or attracts a wider variety of offenders (Ruiter 2017). The variety of businesses on a block may provide a variety of criminal opportunities, resulting in more offenders being attracted to the block (Song et al. 2019), or it may attract a wider variety of persons to the block, making it easier for offenders to blend into the environment. All of these reasons imply that consumer business heterogeneity is expected to result in more crime on the block, and therefore may be important to account for.

H4: There will be a positive relationship between consumer business heterogeneity and violent and property crime

How the broader context impacts the consumer business heterogeneity and crime relationship

Whereas an advantage of much recent crime and place scholarship is the focus on ever smaller geographic units to capture relationships with crime at micro-locations, a general risk of this strategy is failing to account for the context in which such micro-units are embedded. We use our large dataset to address this potential limitation in three different ways. Our first strategy accounts for the business context of the area surrounding each block. This follows from prior research showing that the business context around blocks can impact the crime within them (Hipp and Kim 2019; Hipp, Kim, and Wo 2021; Hipp, Wo, and Kim 2017). The logic is that a block with retail establishments within a commercial district will likely have different crime exposures compared to one situated within a residential area. That is, the concentration of many retail establishments in an area would provide more targets, and therefore be more attractive to offenders, increasing crime opportunities. Likewise, a block with retail establishments, or a mix of such businesses, may be differentially attractive to offenders or potential targets if it is situated in a broader industrial area, or if it is situated in a broader environment characterized by many white-collar businesses. We will capture this by creating measures of consumer-facing, blue-collar, or white-collar businesses in the surrounding ½ mile area as a way to assess the importance of this nearby environment.

H5: There will be a positive relationship between consumer-facing businesses in the surrounding area and block violent and property crime

A second feature of the local context that may impact how consumer business heterogeneity is related to crime is the socio-demographic composition of the surrounding area. Whereas consumer business heterogeneity is expected to impact the numbers of persons in the ambient environment, as noted earlier, the socio-demographic features of this ambient population, and the nearby residents, may impact this relationship. In their study of Southern California, Hipp and Hodgen (2024) tested whether two key features moderate this relationship: the size of the local residential population and the level of concentrated disadvantage in the nearby area. Regarding the size of the residential population, it is expected to negatively impact crime based on the insights of Jane Jacobs (1961), and therefore would moderate the relationship of consumer business heterogeneity and crime. Regarding concentrated disadvantage, social disorganization theory argues that this feature of a neighborhood reduces informal social control and therefore the composition of potential guardians. If this indeed occurs, we would expect to observe a stronger positive relationship between consumer business heterogeneity and crime in blocks surrounded by greater concentrated disadvantage, although Hipp and Hodgen (2024) failed to detect such an effect in Southern California blocks. Similarly, social disorganization theory posits that residential instability and racial/ethnic heterogeneity will reduce informal social control, which would also be expected to increase the positive relationship between consumer business heterogeneity and crime. We will test this possibility as well. Finally, the presence of more persons in the most crime-prone ages living nearby might also increase the strength of this relationship between consumer business heterogeneity and crime, given that such potential offenders would take advantage of these increased crime opportunities. We will therefore assess whether the percentage aged 16 to 29 in the surrounding environment moderate this relationship.

H6: The relationship between consumer business heterogeneity and crime will be moderated by neighborhood-level socio-demographic variables

Given our large dataset across many cities, a final context we will assess is that of the broader city itself. Although our focus will be on relationships with crime in micro-units, we will assess if this relationship between consumer business heterogeneity and crime is moderated in certain city contexts. We will consider five dimensions of the social environment. Two capture the number of people in the environment, specifically the size of the population and the level of population density, given the large body of scholarship positing that these two dimensions impact the amount of crime in a city (Land, McCall, and Cohen 1990; Liska, Logan, and Bellair 1998; Messner and Sampson 1991). There are various possible mechanisms for this, but one was the presumption of Louis Wirth (Wirth 1938) that larger cities will increase a sense of anonymity, which criminological theory predicts could lead to more potential offenders (Hipp and Roussell 2013). An expected consequence of this increase in potential offenders is that the crime opportunities from consumer business heterogeneity would result in increased crime levels in such blocks. Two other dimensions are based on the socio-economic context of the city, as the average income of a city or the level of inequality in a city would both be expected to potentially increase the number of motivated offenders. This inequality is posited to bring about more crime in general, and this may be accentuated at locations with more consumer business heterogeneity. Finally, we assess whether the racial/ethnic heterogeneity of a city moderates the relationship between consumer business heterogeneity and crime.

H7: Several city-level measures will strengthen the relationship between consumer business heterogeneity and crime

Data and methods

Data

This study uses data in blocks across 182 cities in the United States with a population of at least 50,000. We combined data collected from police agencies with socio-demographic data from the U.S. Census and business data from the Reference USA Historical Business Dataset.

Dependent variables

The crime data come from the National Incident Crime Study (NICS). The NICS is a large-scale project collecting incident crime data from a large number of cities. The crime data for a small number of cities were collected directly from the agencies, whereas much of the data were obtained from public use websites of the police agencies. Crime data were also collected from various open data websites and the website provided by ESRI (https://opendata.arcgis.com/datasets).[1] Some data were also collected from the now-defunct MOTO website (https://moto.data.socrata.com/api/views/). A set of cities in southern California come from the Southern California Crime Study (SCCS). For the present study, we classified crime incidents into four Uniform Crime Report (UCR) categories: aggravated assault, robbery, burglary, and motor vehicle theft. We did not include homicides, given that their rareness makes estimating such micro-scale models impractical, and did not include larcenies given that they are relatively minor crimes, and tend to be spatially similar to the other property crimes (burglaries and motor vehicle thefts). We averaged crime incidents from 2009-11 to smooth over yearly fluctuations. Crime incidents were geocoded for each city separately to latitude–longitude point locations using ArcGIS 10.2, and subsequently aggregated to blocks, with geocoding match rates above 90% in the cities.[2] These data have been used in prior research (Kubrin, Luo, and Hipp 2024).

Independent variables

Our key independent variables capture the presence of businesses on blocks. We geocoded each business and placed it in its appropriate block. To account for different-sized businesses on a block, we followed prior research and constructed a measure of the *logged* employees (we add one before logging, and then add 1 after logging) in each business on a block, and then summing these logged counts (Hipp and Hodgen 2024). This strategy yields a value of 1 for a firm with no employees (a sole proprietor), and larger firms will be weighted

[1] As part of the data cleaning, it was also checked and confirmed that the crime cleaning resulted in crime totals for the cities that were generally within 5% of the reported totals by the city to the FBI for the UCR data.
[2] While some prior research using calls for service finds a substantial number of incidents that occur at intersections, this was not the case for these data as there were very few incidents located to intersections. This is consistent with prior research and expectations as we would not anticipate many serious crimes to occur at intersections, which tend to be busier.

more, but not as much as if simply counting the number of employees instead of logged employees.

We followed earlier research and classified businesses based on the 6-digit North American Industry Classification System (NAICS) code. We created a measure of consumer-facing businesses based on whether the business primarily serves the public as customers, with 31 classes of consumer-facing businesses (Kane, Hipp, and Kim 2017).[3] We created a measure of *consumer business heterogeneity* as a Herfindahl Index of these 31 business types; this is computed as 1 minus a sum of squares of the proportions of each of these types (Hipp and Hodgen 2024). We classified nonconsumer businesses into *white-collar businesses* (e.g., office-based) and *blue-collar businesses* (e.g., factories and light industry) based on the 2-digit NAICS code.[4]

We also tested whether blocks with specific types of businesses experience more crime. We began with these 31 types of consumer-facing businesses, and estimated models in which we included all of these variables and the control variables, but did not include our key measures of the business context. We determined that 12 of these types of establishments exhibited consistently quite strong positive relationships with our four types of crime in these models. We therefore maintained these 12 types of businesses in our displayed models: auto services; alcohol establishments; child care; convenience stores; drinking establishments; drug stores;

[3] These classes are the following: Apparel Retailing; Auto Services; Beer, Wine, and Liquor Stores; Child Care Services; Convenience Stores; Deposit-taking Institutions; Drinking Places (Alcoholic Beverages); Drug Stores; Elementary and Secondary Schools; Full-Service Restaurants; Gas Stations; General Merchandise Retailing; Groceries; Hair Care Services; Healthcare Provider Offices; Home Products Retailing; Hospitals; Laundry; Limited-Service Food and Beverage; Medical Laboratories; Movie Theaters; Other Learning; Other Personal Services; Personal Financial; Personal Products Retailing; Recreational Facilities and Instruction; Religious Organizations; Repair Services; Social Service Organizations; Specialty Food; Specialty Retailing

[4] We classified as white-collar firms those with the following 2-digit NAICS codes (unless they were already classified as consumer-facing): 51, 52, 53, 54, 55, 56, 92, 99, and the following as blue-collar firms: 11, 21, 22, 23, 31, 32, 33, 42, 48, 49.

elementary/secondary schools; full restaurants; gas stations; general merchandise stores; grocery stores; religious establishments. Nearly all of these are establishments which prior theory would expect to be associated with elevated crime levels on blocks. The one exception are religious establishments—however, these showed such robust relationships in these early models that we maintained this measure in our final models. This also allows us to demonstrate the peril of estimating such models without accounting for the general business context.

In addition to the aforementioned measures capturing the business context of the specific block, we also included three variables capturing the business context of the environment surrounding the block. These measures aggregate employees within a ½ mile buffer of the block based on an exponential decay function. These are the same three aggregated business variables as measured in the block: consumer-facing employees, white-collar employees, and blue-collar employees (all log transformed).[5]

Control variables

We account for the socio-demographic environment by constructing several measures that are centered on the block and have an exponential decay function capped at ¾ mile. This strategy arguably more appropriately captures the nearby environment—rather than simply using defined census units such as tracts—and avoids the problem of block-level variables in which the large number of blocks with no population results in much missing data. These measures are constructed from the 2010 U.S. Census and the American Community Survey (ACS) 5-year estimates for 2008-12. For variables that are only available in larger units, such as block groups or tracts, we imputed them to blocks using the ecological inference approach that incorporates

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[5] These are measured as employees rather than as logged employees per business since employees satisfactorily capture the business environment in this larger area. It is only at the more precise spatial scale of blocks where it is necessary to account for both the number and size of businesses.

other characteristics of the block, given evidence that this yields results preferable to a simple areal imputation (Boessen and Hipp 2015).[6]

We constructed a measure of *concentrated disadvantage* based on a factor score from a principle components analysis of percent at or below 125% of the poverty level, average household income, percent with at least a bachelor's degree, and percent single parent households. We captured r*esidential stability* as a factor score based on a principle components analysis of percent owners, percent in same house 1 year ago, and average length of residence. We included measures of the racial/ethnic composition: *percent Black*, *percent Asian*, and *percent Latino* (with percent White and other as the remaining category). We measure *racial/ethnic heterogeneity* as a Herfindahl index of these same five racial/ethnic categories. Given that they can provide crime opportunities, we measured *percent vacant units*, and we included the *percent aged 16 to 29* as potential offenders. The residential population is measured as *population (logged after adding 1)*. The summary statistics for the variables used in the analyses are shown in Table 1.

<<<Table 1 about here>>>

Methods

To account for the overdispersion of the count outcome variables, we estimated negative binomial regression models for the four crime types with city fixed effects. These models are estimated as:

$$E(y) = \exp(\alpha + B_1 X_B + B_2 X_S + B_3 C + \mu) \tag{1}$$

[6] The synthetic estimation for ecological inference imputes values to blocks based on the relationships between variables at the higher geographic unit of analysis (Cohen and Zhang 1988; Steinberg 1979). We used these variables in the imputation model: percent owners, racial composition, percent divorced households, percent households with children, percent vacant units, population density, and age structure (percent aged: 0-4, 5-14, 15-19, 20-24, 25-29, 30-44, 45-64, 65 and up, with age 15-19 as the reference category).

where y is the count of crime events in the block, $\boldsymbol{X_B}$ contains the various business variables, X_S contains the various socio-demographic variables, C is a vector of city indicator variables, $\mathbf{B_1}$, and $\mathbf{B_2}$ and $\mathbf{B_3}$ are vectors of parameters capturing the relationships between these measures and the crime count, and μ is a parameter capturing the overdispersion based on a gamma distribution.

For each outcome variable, we estimate a series of five models, all of which include our control variables. These models are: 1) the 12 business types; 2) our four aggregated business measures; 3) the four aggregated business measures and the three nearby businesses measures; 4) the four aggregated business measures and the 12 business types; 5) all of the business variables. We tested for nonlinear effects by also including quadratic versions of our business context measures; these variables were either nonsignificant, or exhibited very modest bends when plotted, so we only present the linear results. The variables in the models all had variance inflation factor values below 5, indicating no collinearity concerns, especially given the size of the sample (O'Brien 2007).

In the moderation analyses, we tested whether our consumer business heterogeneity variable has differential effects across different types of cities. Although a complete multilevel analysis is outside the scope of the current study, we tested city fixed effects models along with the interaction of our consumer business heterogeneity variable with five city-level variables: population size (logged); population density; racial/ethnic heterogeneity; average household income; income inequality. In a fixed effects model, it is not possible to include the city-level main effects given that the model is effectively accounting for all non-changing differences across cities, but it is appropriate to include the interaction variables to assess the extent to which block-level consumer business heterogeneity varies across these five particular city contexts (Bollen and Brand 2010).

We also tested whether the consumer business heterogeneity variable is moderated by the socio-demographic composition of neighborhoods. For these models, we included interactions between the consumer business heterogeneity variable and: concentrated disadvantage; residential stability; percent aged 16 to 29; racial/ethnic heterogeneity; and logged population. Although several interactions were statistically significant, most were substantively quite small when plotted. The one consistent exception was for logged population (and the quadratic), and we plot those results when we present them later. For all interaction models, we tested one interaction term at a time.

Results

Comparing model fit across model specifications

We first compare the model fit across the five different model specifications for each crime outcome. The pseudo R-square values for each model are displayed in Table 2, and the first column shows the results for the five models with aggravated assault as the outcome variable. In model 1 with the 12 specific types of businesses in the block, we see that this is the poorest fitting model for aggravated assault with a pseudo R-square of .117. When we instead use our four aggregated business variables in the block in model 2 the model fit is improved considerably to .132. This highlights the importance of accounting for the general business context of a block, rather than simply focusing on specific types of businesses. We see a similar result for the other three types of crime, as the pseudo R-square improves between model 1 and model 2 from .147 to .168 for robbery, from .06 to .078 for burglary, and from .089 to .11 for motor vehicle theft. In model 3 we also included the three variables capturing the business environment in the surrounding ½ mile buffer, and there is essentially no model fit improvement for motor vehicle theft. However, there is some modest improvement in pseudo R-square of .001 to .004 for the other crime types. In model 4 we added the 12 business types to model 2 with the block aggregated business measures, and we see only a very modest improvement in pseudo R-square of from .001 to .004. Model 5, which includes all of the business measures, only shows a very modest fit improvement compared to the other models. Given that there are few differences in the remaining variables when introducing the spatially lagged business variables, in the subsequent sections we only display the models with the aggregated business variables that include the spatially lagged business variables (models 1, 3, and 5 in Table 2).

<<<Table 2 about here>>>

Violent crime models

We next describe the model results for the two violent crime outcomes of aggravated assault and robbery. In the first model (this was model 3 from Table 2), we include our four aggregated business variables and the three spatially lagged business variables, along with the control variables. Given that the business variables are logged, the negative binomial model allows us to interpret the coefficients as percent changes. Thus, there is a strong relationship between consumer-facing businesses and violent crime, as a 10 percent increase in these businesses is associated with 3.5% more aggravated assaults and 4.2% more robberies (see model 1 in Table 3). There is a slightly weaker relationship for white-collar businesses, as a 10 percent increase is associated with 2.6% more aggravated assaults and 2.1% more robberies. However, there is a much weaker relationship between blue-collar businesses and aggravated assault, and no relationship with robberies. Consistent with an earlier study of Southern

California, there is strong evidence that greater consumer business heterogeneity on the block is associated with more violence. A one standard deviation increase in consumer business heterogeneity is associated with 6% more aggravated assaults and 17% more robberies.

<<<Table 3 about here>>>

Regarding the business context in the broader ½ mile buffer around a block, only the presence of more consumer-facing employees in that area is associated with more violent crime. However, it is a quite modest effect, as a 10 percent increase in consumer-facing employees in the surrounding area is associated with 0.1% more aggravated assaults and 1.2% more robberies. In contrast, the presence of more white-collar or blue-collar employees in the surrounding ½ mile buffer is actually associated with modestly fewer violent crimes in these blocks.

In model 2 we replaced our aggregated business measures with the variables capturing 12 specific types of businesses, to mimic a common strategy in the literature (this is model 1 in Table 2). We already noted that this model has a much worse fit. Furthermore, it is notable that these 12 types of businesses tend to show very strong positive relationships with aggravated assault and robbery. However, a limitation to this model is that it does not account for the general business context of each block. In model 3 (this was model 5 in Table 2), we also included our four aggregated business measures on the block, as well as the three measures capturing the business environment of the surrounding ½ mile buffer. In this model, we see that the size of the coefficients for the 12 types of businesses are reduced dramatically, and in some instances a positive relationship reverses to a negative one.

The results of model 3 indicate that it is not appropriate to attribute the crime incidents on a block to the specific business type, but rather that they are mostly due to the more general business context. For example, the positive coefficients for auto services businesses evaporate and become slightly negative. For alcohol establishments, the coefficients are reduced 70-80% when accounting for the business context. The coefficients for child care businesses are reduced 80-100% for these two violent crimes, whereas those for convenience stores or gas stations are cut in half. Drinking establishments are the least impacted in this model, and yet their coefficients are reduced 35-65%. Drug stores and general merchandise stores are no longer positively related to aggravated assaults. The coefficients for schools are reduced 60-80%, those for groceries about 70%, and restaurants about 90%. It is also notable that whereas religious locations appear to be positively related to violence when not accounting for the general business context, this completely evaporates and becomes a slight negative relationship when appropriately accounting for this context. Note also that in model 3 the coefficients for the aggregated business measures in the block and the three nearby business measures are all effectively unchanged from model 1, which did not include these 12 specific types of businesses.

Property crime models

We next turn to the models with the property crime outcome variables of burglary and motor vehicle theft. We see in model 1 of Table 4 for the two property crimes that all four of our aggregated business measures in the block are positively associated with both burglary and motor vehicle theft. The strongest effects are for white-collar establishments, as a 10 percent increase in these businesses is associated with about 3.4% more property crime. A 10 percent increase in consumer-facing businesses is associated with 2.3 to 2.8% more property crime, whereas a similar increase in blue-collar businesses is associated with 1.3 to 1.7% more property crime. A one standard deviation increase in consumer business heterogeneity is associated with 2.2 to 3.3% more property crime. We again see that the presence of more white- and blue-collar employees in the surrounding area is associated with less property crime. Whereas blocks surrounded by more consumer-facing employees experience more motor vehicle thefts, they experience fewer burglaries.

<<<Table 4 about here>>>

In model 2 for burglary and motor vehicle theft in Table 4, we see that there are strong positive relationships between the 12 specific business types and these property crimes when not accounting for the general business context of these blocks. These results in model 2 are biased upwards given that they do not account for this business context, and are greatly diminished in model 3 when accounting for it. Nearly all of these coefficients are reduced at least by half, and often much more. The positive relationships between several of these specific business types and property crime in model 2 are essentially completely eliminated in model 3 when including the general business context, including for auto services, alcohol establishments, drug stores, full restaurants, and groceries. Thus, there is only modest evidence that blocks with certain types of businesses have more property crime once accounting for the general business environment: most notably, blocks with more convenience stores, schools, gas stations, and general merchandise stores experience somewhat elevated property crime rates even when accounting for the general business context.

Finally, we observe that our control variables generally had the expected directions for their relationships with crime. Blocks surrounded by more concentrated disadvantage, racial/ethnic heterogeneity, percent Black, and vacant units generally experience more violent and property crime. Blocks surrounded by more Latinos have fewer burglaries but higher levels of the other three crime types. There is a nonlinear relationship between the population in the surrounding area and crime. Plotting this showed that this is an increasingly positive relationship (not shown) as crime increases the most at the highest population concentrations.

Moderation analyses of consumer business heterogeneity

Given the evidence that, consistent with earlier research, the level of consumer business heterogeneity on a block was positively associated with crime, we next tested whether this coefficient was moderated by a few key city-level measures. For four of the city-level measures (racial/ethnic heterogeneity, average household income, income inequality, and population density), the interaction terms were either nonsignificant, or substantively unimportant when plotted. However, we detected strong interaction effects between the consumer business heterogeneity variable and the size of the city population. We measured this based on the average population within 5 miles of each tract in a city (logged), following prior research (Hipp and Roussell 2013), as this better captures the population in the broader environment rather than using city boundaries, which can be arbitrary and ignore large populations just outside of city boundaries.

We plot the results of these interactions in Figure 1 for the four crime types. These plots show each variable at low (one standard deviation below the mean), average (the mean), and high (one standard deviation above the mean) levels. The consistent pattern is that the positive relationship between consumer business heterogeneity and all four types of crime is strongest in small population cities, and weakest in large population cities. This is contrary to hypothesis 7, which hypothesized a stronger positive relationship in large cities. For the two violent crimes, the positive relationship between consumer business heterogeneity and assaults and robberies is weakest in large population cities (the lowest line in these figures). For the two property crimes, the positive relationship actually evaporates in large population cities and becomes slightly negative. In contrast, the steepest positive relationship between consumer business heterogeneity and crime occurs in smaller population cities. Why this relationship is weaker in larger cities, but stronger in smaller cities, is not immediately apparent based on existing theory, but should be a focus of future research.

<<<Figure 1 about here>>>

Finally, we tested whether the relationship between the consumer business heterogeneity variable and crime levels is moderated by various neighborhood characteristics. Although several interactions were statistically significant, the plotted results did not demonstrate a substantial interaction effect. The exception were the interactions with the size of the residential population nearby. This measure (and the quadratic term) exhibited a substantial interaction effect with the consumer business heterogeneity measure, and these are plotted in Figure 2. In Figure 2A for aggravated assault, we see that the strongest positive effect for consumer business heterogeneity occurs in areas with a small residential population (the left hand side of the figure). This can be seen based on the gap between the three lines, with the highest line (the dotted line) showing the aggravated assaults for a block with high consumer business heterogeneity. As the residential population increases, the number of aggravated assaults increases (moving towards the right side of the figure); however, the difference between high and low consumer business heterogeneity blocks evaporates. The story is the same for robberies in Figure 2B and burglaries in Figure 2C. The pattern is most extreme for motor vehicle thefts in Figure 2D, as the number of motor vehicle thefts in high consumer business heterogeneity blocks remains effectively unchanged regardless of the size of the residential population (the effectively flat dotted line). Thus, there are more motor vehicle thefts in low population blocks with high consumer business heterogeneity (the left side of the figure), but fewer motor vehicle thefts in high population blocks with high consumer business heterogeneity (the right side of the figure). One possible explanation is that vehicles are at more risk in low population blocks as they may be parked in unmonitored parking lots, but we cannot say if this is the reason this relationship is observed.

<<<Figure 2 about here>>>

Discussion

This study has reinforced the results from an earlier study in the Southern California region that the context of businesses on a block has important consequences for understanding where crime occurs (Hipp and Hodgen 2024). Using blocks in 182 cities across the U.S., the present study demonstrated that existing studies measuring only a few specific types of businesses on a block—and not accounting for the general business context—yield biased results. We showed consistent results in which the size of coefficients for specific types of businesses were almost always reduced by at least 50% when accounting for this general business context, and often much more than this. The relationships with crime for several specific types of businesses were completely eliminated when accounting for the general business context. The conclusion is that higher levels of crime on these blocks cannot be attributed to these specific businesses, but rather is due to the general business context. Simply measuring the number of consumer-facing businesses, white-collar businesses, and blue-collar businesses—along within a measure of heterogeneity among consumer businesses—captures most of the variation in crime due to businesses across the blocks of this large sample.

One key finding that mimicked an earlier study of Southern California blocks, and was consistent with hypothesis 1, was that the predictive power of specific business types for where crime occurs is considerably reduced when accounting for the general business context of a block (Hipp and Hodgen 2024). In the present study, we included businesses that are particularly likely to be associated with elevated crime levels, and yet their effects were greatly reduced when accounting for the general business context of the block and some were completely eliminated. There were only a few exceptions, as blocks with more convenience stores, drinking establishments, gas stations, and schools have somewhat higher levels of crime even when accounting for the general business context. Nonetheless, we showed that the size of these relationships will be greatly overestimated if the general business context is not accounted for. This raises a caution for future research wishing to establish the relationship between specific business types and crime, and highlights the need to simultaneously account for the general business context.

Another finding consistent with that earlier study of Southern California blocks was that the general business context can be well captured with just four variables. A measure of consumer-facing businesses on the block captures the types of businesses that attract patrons, and therefore would be expected to increase the confluence of offenders and targets on a block. Indeed, we found that this measure was associated with higher levels of crime on a block, especially violent crime, which is consistent with hypothesis 2 and with the earlier study of Southern California blocks (Hipp and Hodgen 2024). These businesses attract many customers to them, in addition to the workers, which would explain why they are associated with more crimes against persons. Thus, extant literature finding a positive relationship between specific types of business and crime in blocks is arguably simply capturing the effect of how such businesses draw people to an area, and not capturing anything unique about the specific businesses. We also found, consistent with hypothesis 3, that a measure of white-collar businesses on a block was consistently associated with higher levels of crime on blocks, especially property crime. This effect for property crime was even stronger than that found in an earlier study of Southern California blocks. Whereas these types of businesses are typically not a focus of crime and place studies, the evidence here suggests that the opportunities they provide for crime should not be overlooked. Likewise, the presence of blue-collar businesses on a block were associated with elevated property crime levels, which echoed the findings of an earlier study of Southern California blocks. Again, this suggests that these businesses provide opportunities for vehicle thefts or burglaries, even if there was less evidence that they are associated with more violent crime. Notably, there was little evidence that these three business context measures have nonlinear relationships with crime, despite possible theoretical reasons for expecting this (Hipp and Hodgen 2024). Thus, whereas such locations might increase the ambient population, which could increase both offenders and targets, it could also increase the presence of passive guardians, which a simulation study found implied a nonlinear relationship (Birks and Davies 2017). Nonetheless, the results here also replicate the earlier Southern California study that tested and found very modest nonlinear relationships with crime. These three measures—along with our measure of consumer business heterogeneity—generally well captured the business environment of blocks, and adding measures of the 12 specific businesses we focused on added very little explanatory power.

Another important result was our evidence of a positive relationship between consumer business heterogeneity and crime, which was consistent with hypothesis 4 and replicates an earlier study focused only on Southern California blocks (Hipp and Hodgen 2024). That earlier study noted that whereas Jane Jacobs hypothesized that consumer business heterogeneity would increase guardianship, and therefore reduce crime, greater consumer business heterogeneity might also increase the number of potential targets and offenders on a block, leading to more crime (Birks and Davies 2017). Similar to that earlier study, we found that such blocks consistently have more crime based on a measure of consumer business heterogeneity using 31 categories of consumer-facing businesses. Nonetheless, the size of the coefficients for this measure in the present study were somewhat smaller compared to that earlier study. This may imply that this consumer business heterogeneity has differential effects across various macro settings. As a preliminary assessment of this possibility, our moderation analyses tested this for five particular city-level characteristics, and found consistent evidence that the consumer business heterogeneity measure has a stronger relationship with crime in *smaller* cities. This finding contradicted our hypothesis 7. Why this relationship is weaker in larger cities is unclear and is a question outside the scope of the current research project, but is a useful direction for future research. We also tested and found that this relationship was weaker in blocks with more residential population, which was consistent with hypothesis 6 and results from the earlier study in Southern California. Thus, it appears that consumer business heterogeneity is most crime enhancing on blocks when there are fewer residents nearby, or when they are located in smaller cities. Exploring the mechanisms of this relationship will be a needed direction for future research.

One final contribution of the present study was accounting for the business context in a ½ mile buffer around the block. Notably, contrary to hypothesis 5, we found minimal evidence that this business context increases the amount of crime on a block. In fact, blocks surrounded by more white-collar and blue-collar employees consistently have slightly lower levels of violent and property crime. The implication is that such business districts actually reduce the amount of crime on the blocks within them. Of course, the specific blocks with businesses still have elevated crime due to their own business context. Nonetheless, it may be that the presence of residential areas nearby—rather than a business district—increases crime due to the increased potential for offenders to access the block given the relative nearness of these businesses. In contrast, there was modest evidence that a block within a commercial district actually has somewhat more violent crime and motor vehicle thefts. Similar to the economies of scale that shopping malls obtain in which they often have more shoppers than would a single business on a block, it may be that such locations provide more crime opportunities and therefore attract offenders (Brantingham and Brantingham 1984). Nonetheless, in ancillary models we tested whether blocks with more consumer business heterogeneity have higher crime levels when they are surrounded by commercial districts, and there was no such evidence.

We acknowledge some limitations to this study. The cross-sectional design of our study limits us to observing relationships, and we cannot say whether these are causal effects that we observe. We also did not explore potential mechanisms, so we are unable to say why we observe these relationships. For instance, we do not account for the presence (or type) of offenders (or the ambient population more broadly). As such, we cannot determine whether the relationship between consumer business heterogeneity is positively associated with crime because the mix of businesses offers a variety of criminal opportunities or whether there is some other mechanism operating.

In conclusion, the results of this study reinforce the evidence from an earlier study of the necessity for scholars to measure the business context on blocks (Hipp and Hodgen 2024). Our results highlight that extant research focusing on the relationship between specific types of businesses and crime can yield quite biased results if they do not account for the general business context of those blocks. Once accounting for the general business context of these blocks, the strength of the relationships for 12 specific types of businesses were greatly reduced, and often completely eliminated. The fact that we found these results across a very large sample of blocks in 182 cities with a population of at least 50,000 emphasizes the robustness of these results. It was encouraging that we could measure the number of businesses in just three broad categories—consumer-facing businesses, white-collar businesses, and blue-collar businesses—and explain much of the variance in crime due to businesses across blocks. Furthermore, we showed that the heterogeneity of consumer-facing businesses on a block is positively related to the amount of crime on a block, a feature of the environment that is relatively new to the literature, and yet appears to have quite important consequences. Scholarship will need to explore the specific mechanisms that bring this about, especially given that this relationship appears most pronounced in smaller cities and on blocks with a smaller residential population.

References
Bernasco, Wim, and Richard L. Block. 2011. Robberies in Chicago: A Block-Level Analysis of the Influence of Crime Generators, Crime Attractors, and Offender Anchor Points. *Journal of Research in Crime and Delinquency* 48 (1):33-57.
Birks, Daniel, and Toby Davies. 2017. Street Network Structure and Crime Risk: An Agent-Based Investigation of the Encounter and Enclosure Hypotheses. *Criminology* 55 (4):900-937.
Boessen, Adam, and John R. Hipp. 2015. Close-ups and the scale of ecology: Land uses and the geography of social context and crime. *Criminology* 53 (3):399-426.
Bollen, Kenneth A., and Jennie E. Brand. 2010. A General Panel Model with Random and Fixed Effects: A Structural Equations Approach. *Social Forces* 89 (1):1-34.
Brantingham, Patricia L., and Paul J. Brantingham. 1993. Nodes, Paths and Edges: Considerations on the Complexity of Crime and the Physical Environment. *Journal of Environmental Psychology* 13 (1):3-28.
Brantingham, Paul J., and Patricia L. Brantingham. 1984. *Patterns in Crime*. New York: MacMillan.
Cohen, Michael Lee, and Xiao Di Zhang. 1988. The Difficulty of Improving Statistical Synthetic Estimation. In *Statistical Research Division Report Series*. Washington, D.C.: Bureau of the Census.
Felson, Marcus. 2002. *Crime and Everyday Life*. Third Edition ed. Thousand Oaks, CA: Sage.
Feng, Shun Q., Eric L. Piza, Leslie W. Kennedy, and Joel M. Caplan. 2018. Aggravating effects of alcohol outlet types on street robbery and aggravated assault in New York City. *Journal of Crime and Justice* 42 (3):257-273.
Gorman, Dennis M., Paul W. Speer, Paul J. Gruenewald, and Erich W. Labouvie. 2001. Spatial Dynamics of Alcohol Availability, Neighborhood Structure and Violent Crime. *Journal of Studies on Alcohol* 62 (5):628-636.
Hipp, John R., and Cheyenne Hodgen. 2024. The ecology of business environments and consequences for crime. *Criminology* 62 (4):859-891.
Hipp, John R., and Young-an Kim. 2019. Explaining the Temporal and Spatial Dimensions of Robbery: Differences across Measures of the Physical and Social Environment. *Journal of Criminal Justice* 60 (1):1-12.
Hipp, John R., Young-an Kim, and James Wo. 2021. Micro-scale, meso-scale, macro-scale, and temporal scale: Comparing the relative importance for robbery risk in New York City. *Justice Quarterly* 38 (5):767-791.
Hipp, John R., and Xiaoshuang Iris Luo. 2022. Improving or Declining: What are the Consequences for changes in local crime rates? *Criminology* 60 (3):480-507.
Hipp, John R., and Aaron Roussell. 2013. Micro- and Macro-environment Population and the Consequences for Crime Rates. *Social Forces* 92 (2):563-595.
Hipp, John R., James Wo, and Young-an Kim. 2017. Studying Neighborhood Crime Across Different Macro Spatial Scales: The Case of Robbery in Four Cities. *Social Science Research* 68 (1):15-29.
Jacobs, Jane. 1961. *The Death and Life of Great American Cities*. New York: Random House.
Kane, Kevin, John R. Hipp, and Jae Hong Kim. 2017. Analyzing Accessibility using Parcel Data: Is there Still an Access-Space Tradeoff in Long Beach, California? *The Professional Geographer* 69 (3):486-503.

Kubrin, Charis E., and John R. Hipp. 2016. Do Fringe Banks Create Fringe Neighborhoods? Examining the Spatial Relationship between Fringe Banking and Neighborhood Crime Rates. *Justice Quarterly* 33 (5):755-784.
Kubrin, Charis E., Xiaoshuang Iris Luo, and John R. Hipp. 2024. Immigration and Crime: Is the Relationship Nonlinear? *British Journal of Criminology* Forthcoming.
Land, Kenneth C., Patricia L. McCall, and Lawrence E. Cohen. 1990. Structural Covariates of Homicide Rates: Are There Any Invariances across Time and Social Space? *American Journal of Sociology* 95 (4):922-963.
Liska, Allen E., John R. Logan, and Paul E. Bellair. 1998. Race and Violent Crime in the Suburbs. *American Sociological Review* 63 (1):27-38.
Messner, Steven F., and Robert J. Sampson. 1991. The Sex Ratio, Family Disruption, and Rates of Violent Crime: The Paradox of Demographic Structure. *Social Forces* 69 (3):693-713.
O'Brien, Robert M. 2007. A Caution Regarding Rules of Thumb for Variance Inflation Factors. *Quality & Quantity* 41 (5):673-690.
Roncek, Dennis W., and Pamela A. Maier. 1991. Bars, Blocks, and Crimes Revisited: Linking the Theory of Routine Activities to the Empiricism of 'Hot Spots'. *Criminology* 29 (4):725-753.
Ruiter, Stijn. 2017. Crime Location Choice: State of the Art and Avenues for Future Research. In *The Oxford Handbook of Offender Decision Making*, edited by W. Bernasco.
Scribner, Richard, Deborah Cohen, Stephen Kaplan, and Susan H. Allen. 1999. Alcohol Availability and Homicide in New Orleans: Conceptual Considerations for Small Area Analysis of the Effect of Alcohol Outlet Density. *Journal of Studies on Alcohol* 60 (3):310-316.
Smith, William R., Sharon Glave Frazee, and Elizabeth L. Davison. 2000. Furthering the Integration of Routine Activity and Social Disorganization Theories: Small Units of Analysis and the Study of Street Robbery as a Diffusion Process. *Criminology* 38 (2):489-523.
Song, Guangwen, Wim Bernasco, Lin Liu, Luzi Xiao, Suhong Zhou, and Weiwei Liao. 2019. Crime Feeds on Legal Activities: Daily Mobility Flows Help to Explain Thieves' Target Location Choices. *Journal of Quantitative Criminology* 35 (4):831-854.
Steinberg, Joseph, ed. 1979. *Synthetic Estimates for Small Areas: Statistical Workshop Papers and Discussion*. Vol. 24, *National Institute on Drug Abuse Research Monograph Series*. Washington, D.C.: National Institute on Drug Abuse.
van Sleeuwen, Sabine E. M., Stijn Ruiter, and Wouter Steenbeek. 2021. Right place, right time? Making crime pattern theory time-specific. *Crime Science* 10 (1).
Wilcox, Pamela, Neil Quisenberry, Debra Cabrera, and Shayne Jones. 2004. Busy places and broken windows? Towards defining the role of physical structure and process in community crime models. *The Sociological Quarterly* 45 (2):185-220.
Wirth, Louis. 1938. Urbanism as a Way of Life. *American Journal of Sociology* 44 (1):1-24.

Tables and Figures

Table 1. Summary statistical of variables used in analyses

Dependent variables	Mean	S.D.
Aggravated assaults	0.72	2.11
Robberies	0.59	1.87
Burglaries	1.87	4.37
Motor vehicle thefts	0.98	2.63
Independent variables		
Block-level aggregate business variables		
Consumer-facing businesses (logged)	0.65	1.09
Blue-collar businesses (logged)	0.31	0.70
White-collar businesses (logged)	0.42	0.84
Consumer-facing business heterogeneity	0.11	0.25
Nearby employees (1/2 mile exponential buffers)		
Consumer-facing employees (logged)	1.92	1.12
Blue-collar employees (logged)	4.65	1.75
White-collar employees (logged)	5.10	1.83
Specific business types in block		
Auto services	0.23	1.31
Alcohol	0.02	0.25
Child care	0.07	0.49
Convenience store	0.03	0.30
Drinking	0.04	0.41
Drug store	0.05	0.43
Elementary/secondary schools	0.15	1.04
Full restaurants	0.49	2.54
Gas station	0.04	0.32
General merchandise	0.08	0.71
Groceries	0.08	0.54
Religious	0.18	0.87
Control variables		
Concentrated disadvantage	1.78	9.95
Residential stability	9.54	3.33
Racial/ethnic heterogeneity	0.46	0.18
Percent Black	22.2	28.0
Percent Latino	25.9	25.9
Percent Asian	6.6	9.3
Percent vacant units	10.2	6.8
Percent aged 16 to 29	24.0	8.4
Population density	8.76	1.21
Note: N = 767,747 blocks in 182 cities		

Table 2. Comparing model fit across alternative model specifications

		Aggravated assault	Robbery	Burglary	Motor vehicle theft
1	Block 12 business types	0.117	0.147	0.060	0.089
2	Block aggregate business measures	0.132	0.168	0.078	0.110
3	Block aggregate business measures + nearby businesses	0.133	0.169	0.082	0.110
4	Block aggregate business measures + 12 business types	0.134	0.172	0.078	0.111
5	Block aggregate business measures + nearby businesses + 12 business types	0.135	0.172	0.082	0.111

Note: all models include socio-demographic control variables

Table 3. Negative binomial fixed effects models predicting violent crime in 182 cities, NICS data

	Aggravated assault			Robbery		
	(1)	(2)	(3)	(1)	(2)	(3)
Aggregate business measures						
Consumer facing workers (logged)	0.346 **		0.294 **	0.415 **		0.349 **
	(87.68)		(67.45)	(101.11)		(75.98)
Blue collar workers (logged)	0.043 **		0.051 **	-0.005		-0.005
	(10.69)		(12.45)	-(1.10)		-(1.11)
White collar workers (logged)	0.261 **		0.259 **	0.208 **		0.207 **
	(72.51)		(71.96)	(57.13)		(57.07)
Consumer-facing business heterogeneity	0.218 **		0.153 **	0.616 **		0.471 **
	(13.80)		(9.51)	(38.26)		(28.85)
Spatial lag variables						
Consumer facing workers (logged)	0.009 *		0.010 *	0.115 **		0.108 **
	(2.01)		(2.25)	(24.49)		(23.01)
Blue collar workers (logged)	-0.014 **		-0.014 **	-0.022 **		-0.019 **
	-(5.90)		-(6.01)	-(8.62)		-(7.49)
White collar workers (logged)	-0.046 **		-0.048 **	-0.012 **		-0.008 **
	-(15.62)		-(16.29)	-(3.71)		-(2.69)
Business types						
Auto services		0.068 **	-0.010 **		0.086 **	-0.007 **
		(36.52)	-(6.14)		(43.71)	-(4.28)
Alcohol		0.149 **	0.027 **		0.232 **	0.068 **
		(18.06)	(3.45)		(28.27)	(9.27)
Child care		0.150 **	0.029 **		0.137 **	-0.003
		(34.56)	(7.12)		(31.25)	-(0.64)

Convenience store			0.292	**	0.135	**			0.462	**	0.260	**
			(42.57)		(20.72)				(67.83)		(41.90)	
Drinking			0.281	**	0.176	**			0.202	**	0.070	**
			(51.72)		(36.13)				(36.94)		(15.56)	
Drug store			0.104	**	-0.017	**			0.209	**	0.058	**
			(20.25)		-(3.63)				(41.81)		(13.02)	
Elementary/secondary schools			0.120	**	0.048	**			0.104	**	0.023	**
			(56.84)		(24.02)				(48.76)		(11.72)	
Full restaurants			0.068	**	0.007	**			0.093	**	0.011	**
			(61.95)		(7.33)				(81.89)		(11.41)	
Gas station			0.238	**	0.106	**			0.411	**	0.233	**
			(35.41)		(16.93)				(62.89)		(39.53)	
General merchandise			0.048	**	-0.008	**			0.118	**	0.034	**
			(13.50)		-(2.86)				(33.30)		(12.40)	
Groceries			0.123	**	0.028	**			0.174	**	0.053	**
			(30.52)		(7.40)				(44.19)		(15.14)	
Religious			0.103	**	-0.009	**			0.101	**	-0.032	**
			(37.13)		-(3.74)				(35.96)		-(13.14)	
Concentrated disadvantage	0.051	**	0.050	**	0.052	**	0.044	**	0.038	**	0.044	**
	(89.81)		(86.91)		(91.19)		(72.30)		(63.30)		(72.30)	
Residential stability	0.005	**	-0.006	**	0.004	**	-0.001		-0.022	**	-0.001	
	(4.13)		-(5.37)		(3.70)		-(0.51)		-(17.88)		-(1.08)	
Racial/ethnic heterogeneity	0.468	**	0.420	**	0.471	**	0.702	**	0.633	**	0.694	**
	(24.28)		(21.45)		(24.54)		(34.82)		(30.77)		(34.67)	
Percent Black	0.012	**	0.012	**	0.012	**	0.013	**	0.011	**	0.013	**
	(64.62)		(60.13)		(65.08)		(61.56)		(52.59)		(62.66)	
Percent Latino	0.005	**	0.003	**	0.005	**	0.006	**	0.003	**	0.006	**
	(20.63)		(14.45)		(20.52)		(22.86)		(13.68)		(22.71)	

Percent Asian	-0.006	**	-0.006	**	-0.005	**	-0.002	**	-0.004	**	-0.002	**
	-(13.08)		-(13.33)		-(12.99)		-(3.74)		-(7.82)		-(4.63)	
Percent vacant units	0.019	**	0.018	**	0.018	**	0.012	**	0.020	**	0.012	**
	(32.46)		(32.52)		(31.58)		(19.03)		(32.15)		(19.55)	
Percent aged 16 to 29	-0.002	**	-0.002	**	-0.003	**	0.000		0.002	**	0.000	
	-(5.58)		-(4.71)		-(6.71)		-(0.36)		(5.33)		-(0.30)	
Population (logged)	-0.170	**	-0.212	**	-0.140	**	-0.296	**	-0.425	**	-0.279	**
	-(7.64)		-(9.59)		-(6.25)		-(11.42)		-(16.37)		-(10.55)	
Population (logged) square	0.044	**	0.047	**	0.042	**	0.054	**	0.069	**	0.054	**
	(31.38)		(34.06)		(30.01)		(34.05)		(43.72)		(33.50)	
Intercept	-2.590	**	-2.166	**	-2.680	**	-4.011	**	-3.301	**	-4.122	**
	-(26.31)		-(22.07)		-(27.01)		-(33.74)		-(27.70)		-(33.96)	
Pseudo R-square	0.133		0.117		0.135		0.169		0.147		0.172	
N	735290		735290		735290		767747		767747		767747	
BIC	1347450		1371821		1344346		1181384		1211907		1175901	
Note: N = 767,747 blocks in 182 cities												

Table 4. Negative binomial fixed effects models predicting property crime in 182 cities, NICS data

	Burglary						Motor vehicle theft					
	(1)		(2)		(3)		(1)		(2)		(3)	
Aggregate business measures												
Consumer facing workers (logged)	0.233	**			0.194	**	0.282	**			0.250	**
	(76.24)				(56.51)		(82.71)				(65.28)	
Blue collar workers (logged)	0.173	**			0.176	**	0.130	**			0.124	**
	(57.91)				(58.10)		(38.56)				(36.21)	
White collar workers (logged)	0.339	**			0.340	**	0.328	**			0.327	**
	(124.51)				(124.54)		(106.41)				(106.21)	
Consumer-facing business heterogeneity	0.129	**			0.121	**	0.085	**			0.035	*
	(10.46)				(9.59)		(6.18)				(2.46)	
Spatial lag variables												
Consumer facing workers (logged)	-0.073	**			-0.072	**	0.014	**			0.012	**
	-(23.74)				-(23.36)		(3.68)				(3.28)	
Blue collar workers (logged)	-0.048	**			-0.047	**	-0.014	**			-0.013	**
	-(28.80)				-(28.06)		-(6.74)				-(6.73)	
White collar workers (logged)	-0.074	**			-0.072	**	-0.037	**			-0.036	**
	-(35.54)				-(34.87)		-(14.86)				-(14.56)	
Business types												
Auto services			0.091	**	0.002				0.112	**	0.015	**
			(58.35)		(1.49)				(66.70)		(10.71)	
Alcohol			0.112	**	-0.009				0.091	**	-0.024	**
			(16.34)		-(1.48)				(12.20)		-(3.50)	
Child care			0.152	**	0.044	**			0.137	**	0.022	**
			(43.35)		(13.39)				(35.19)		(6.16)	

Convenience store			0.227	**	0.085	**			0.250	**	0.110	**
			(40.15)		(16.13)				(40.43)		(18.95)	
Drinking			0.082	**	0.002				0.162	**	0.061	**
			(17.90)		(0.46)				(32.96)		(14.02)	
Drug store			0.095	**	-0.009	*			0.090	**	-0.029	**
			(22.85)		-(2.47)				(19.89)		-(6.95)	
Elementary/secondary schools			0.095	**	0.031	**			0.082	**	0.014	**
			(55.42)		(19.69)				(43.44)		(7.85)	
Full restaurants			0.051	**	0.003	**			0.061	**	0.001	
			(58.19)		(3.40)				(63.32)		(1.64)	
Gas station			0.174	**	0.053	**			0.241	**	0.122	**
			(32.50)		(10.68)				(41.59)		(22.69)	
General merchandise			0.068	**	0.017	**			0.086	**	0.037	**
			(23.49)		(7.00)				(28.54)		(15.11)	
Groceries			0.086	**	-0.001				0.080	**	-0.006	†
			(25.60)		-(0.46)				(22.56)		-(1.73)	
Religious			0.128	**	0.023	**			0.107	**	-0.002	
			(56.90)		(10.89)				(43.27)		-(0.71)	
Concentrated disadvantage	0.026	**	0.023	**	0.026	**	0.031	**	0.029	**	0.031	**
	(67.70)		(58.29)		(67.07)		(66.65)		(61.45)		(65.98)	
Residential stability	0.023	**	0.015	**	0.022	**	-0.007	**	-0.021	**	-0.007	**
	(28.57)		(18.53)		(28.29)		-(7.29)		-(22.38)		-(7.57)	
Racial/ethnic heterogeneity	0.533	**	0.488	**	0.528	**	0.390	**	0.374	**	0.381	**
	(39.01)		(34.42)		(38.66)		(24.09)		(22.51)		(23.57)	
Percent Black	0.006	**	0.006	**	0.005	**	0.008	**	0.007	**	0.008	**
	(41.59)		(45.80)		(40.77)		(47.90)		(40.25)		(47.84)	
Percent Latino	-0.002	**	-0.002	**	-0.002	**	0.007	**	0.005	**	0.007	**
	-(10.51)		-(11.90)		-(10.58)		(37.32)		(27.57)		(36.98)	

Percent Asian	-0.002	**	-0.001	**	-0.002	**	0.004	**	0.003	**	0.004	**
	-(8.03)		-(3.49)		-(8.03)		(11.49)		(9.09)		(11.52)	
Percent vacant units	0.004	**	-0.002	**	0.004	**	-0.002	**	0.001		-0.002	**
	(9.38)		-(4.10)		(10.19)		-(3.63)		(1.05)		-(3.00)	
Percent aged 16 to 29	-0.001	**	-0.003	**	-0.001	**	0.003	**	0.004	**	0.003	**
	-(2.72)		-(10.56)		-(2.68)		(7.95)		(11.98)		(8.12)	
Population (logged)	0.011		-0.003		0.018		-0.127	**	-0.170	**	-0.123	**
	(0.76)		-(0.18)		(1.27)		-(8.57)		-(11.54)		-(8.17)	
Population (logged) square	0.035	**	0.029	**	0.035	**	0.029	**	0.031	**	0.030	**
	(37.86)		(32.11)		(37.17)		(29.72)		(32.23)		(29.61)	
Intercept	-3.145	**	-2.706	**	-3.176	**	-2.598	**	-2.061	**	-2.634	**
	-(49.39)		-(42.76)		-(49.68)		-(38.29)		-(30.49)		-(38.38)	
Pseudo R-square	0.082		0.060		0.082		0.110		0.089		0.111	
N	762959		762959		762959		752534		752534		752534	
BIC	2481165		2539250		2480121		1727250		1769307		1725647	
Note: N = 767,747 blocks in 182 cities												

Figure 1. Interaction plots for marginal effects between block consumer business heterogeneity and city population (logged)

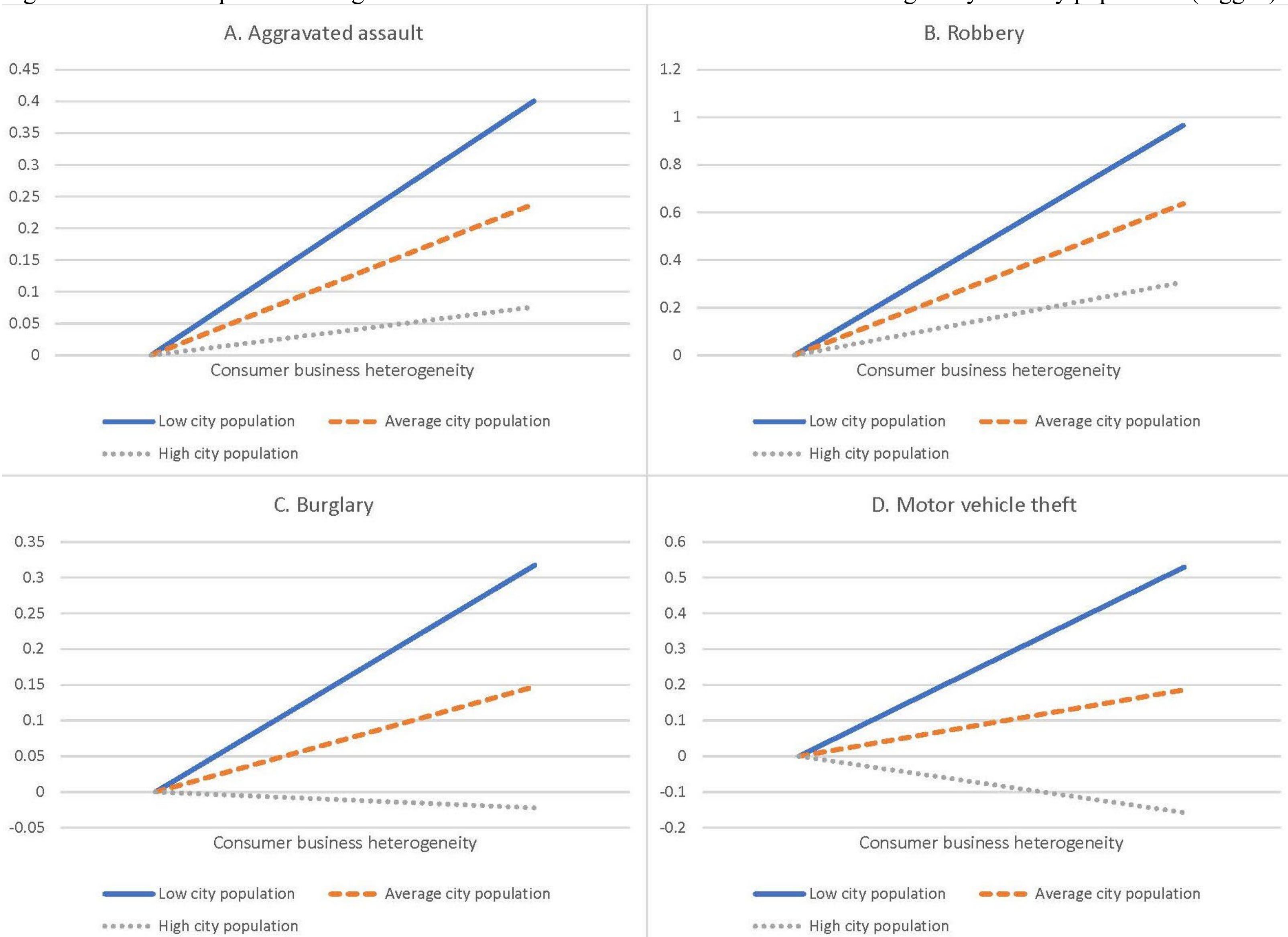

Figure 2. Interaction plots for marginal effects between block consumer business heterogeneity and nearby population (logged)