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IS CRIME BAD FOR BUSINESS? CRIME AND COMMERCIAL PROPERTY VALUES IN NEW YORK CITY*

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ABSTRACT. To test how crime affects economic activity, we use point-specific data on crime, commercial property sales and assessed values from New York City, relying on an instrumental variables strategy. We find that crime reduces commercial property values, and the magnitude of the effect depends on the type and geography of crime. Elasticities range from −0.1 to −0.5. We find stronger evidence for negative violent crime effects in neighborhoods with lower incomes and higher shares of minority residents. Thus, disadvantaged neighborhoods are doubly harmed by crime—they have higher crime rates and those crimes have stronger effects on economic activity.

1. INTRODUCTION

Crime and economic activities are not evenly distributed across urban areas. Neighborhoods besieged by crime are often areas that also lack a number of amenities, including thriving businesses. Having fewer neighborhood commercial establishments deprives residents of nearby employment opportunities and the ability to conveniently procure food, clothing, and other important goods and services. A lot of research analyzes the extent to which reduced economic activity affects crime in cities, metropolitan areas, and neighborhoods, and finds that economic decline in cities and neighborhoods leads to higher crime. However, we do not know much about whether, and how, crime affects economic activity. This paper attempts to address this gap, using commercial property values as a proxy for a neighborhood's economic vibrancy. Using point-specific crime data and commercial property values in New York City from 2004 to 2010, we test whether crime affects the price that individuals and/or firms are willing to pay for commercial real estate.

There is relatively consistent evidence that crime can influence residential property values and location choices, but does this relationship look different for commercial landowners and businesses? How does crime factor into the cost-benefit analysis for commercial properties? Crime can increase the cost of business and can scare off potential customers, all of which should be capitalized into the value of the commercial property. It is unclear whether this prediction plays out empirically and if so, to what extent.

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Struggling neighborhoods—where crime rates are often the highest—are targets of many economic development efforts. It is important to know how crime might affect some of these improvement efforts, and if crime-control itself can be a viable economic development tool. There are stark disparities across neighborhoods in the access to commercial amenities (and local employment opportunities); our work aims to shed light on whether these inequalities are exacerbated by differential exposures to crime and what crime means for urban neighborhood development more broadly.

An important advantage of this paper is that we employ instrumental variables to estimate crime's effect, mitigating endogeneity due to the fact that business activity affects crime just as crime may affect business activity. We also aggregate crime to three fine-grained levels of geography: (i) the blockface (both sides of a city block), (ii) the "H-block," which is a set of blockfaces that surround a property sale located in the center of the block grid (see Figure 1), and (iii) a more commonly used geographic "ring," or quarter-mile buffer, around the property. Our instrumental variables—changes in employment rates and precinct crime rates—predict the likelihood of criminal activity, but are not correlated with commercial property values, controlling for other property-level and geographic characteristics.

Results suggest that crime does reduce commercial property values, and the magnitude of the effect varies depending on the type of crime and the geography of crime. Analyses using property transactions show no significant crime effects at very close range; an additional violent or property crime, however, within a quarter-mile of the property reduces prices by 0.5 and 0.2 percent, respectively. In analyses using assessed values, negative crime effects are discernible at very close range (i.e., on the same blockface), such that an additional crime reduces prices by 2 to 6 percent, depending on the type of crime. Given that the average sales price is much higher than the average assessed value, these effect sizes are quite comparable in absolute dollar terms. The crime effects remain negative and become slightly smaller at larger multiblock crime geographies: an additional crime results in a 0.4 to 1 percent price drop. In low-income and high-minority neighborhoods, where the findings are more pronounced, we find that crime-induced price declines are driven by violent crimes. These effects suggest that crime is further deterring commercial investment in otherwise disadvantaged neighborhoods.

This paper proceeds in the following way. Section 2 discusses the theoretical intuition behind why and how crime might affect commercial activity. Section 3 reviews the relevant empirical literature. Section 4 presents the data and methodology and Section 5 presents the results. Section 6 concludes and describes policy implications.

2. HOW MIGHT CRIME AFFECT COMMERCIAL PROPERTY VALUES?

Crime in U.S. cities has declined substantially since the 1990s, and New York City is perhaps the best example of the crime decline. In New York City, homicide rates declined nearly 74 percent between 1990 and 2001, a more drastic drop from peak levels than any other large city (Levitt, 2004). These declines were unprecedented in New York City history and the declining crime trends continued into the 2000s (between 1998 and 2009, the homicide rate fell another 34 percent, according to a 2010 report from the New York City Police Department). And even in the midst of a global recession, crime rates continued to fall.

Despite these persistent crime declines, many neighborhoods in U.S. cities continue to be plagued by high levels of crime and violence. Across the 96,000-plus city blocks in New York City, for example, the median total number of violent crimes per block in a year is less than one. However, there are three times as many crimes in the top 10 percent of

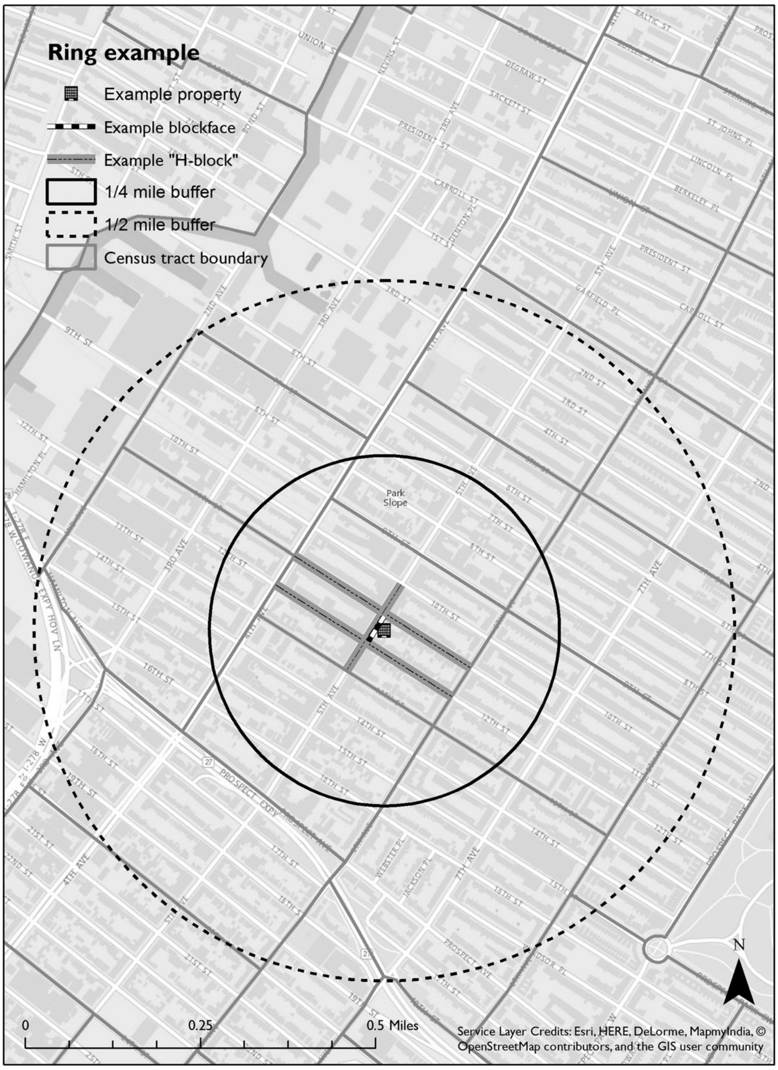

FIGURE 1: Geographies of Crime, Visual Illustration.

crime-ridden blocks and over nine times as many crimes in the top 1 percent. For major property crimes, the median block has one crime per year, yet the top 10 percent has over seven crimes and the top 1 percent has over 30 crimes per year. In addition, huge disparities still exist between different demographic groups. For example, nationwide, blacks are three times as likely as whites to be a victim of homicide (Parker, 2008). In New York City, predominantly black and Hispanic neighborhoods have more than twice the crime rates than predominantly white neighborhoods. These neighborhoods also have significantly fewer and less vital commercial establishments (Meltzer and Schuetz, 2012).

Crime Increases Costs and Decreases Revenues for Businesses

There are a number of reasons why we would expect higher levels of crime to lead to reduced economic activity. Business location decisions are a function of fixed start-up costs and variable factors that drive potential revenues (Hotelling, 1929). On the revenue side, crime may deter potential customers and reduce demand. Neighborhood crime may also increase operation costs. Businesses in these neighborhoods may have to hire security personnel to safeguard merchandise or employees during or outside the hours of operation. Additional labor costs may also come from having to pay higher wages to employees to compensate them for the higher risk of working in dangerous locations. Property theft may also raise operation costs. Businesses may also find that insurance premiums are higher in these neighborhoods, reflecting the higher likelihood of theft or injury to employees and customers.

Given such potential negative effects on revenues, we would expect crime rates to discount the price that businesses are willing to pay for a given commercial space. If we observe that increases in crime lead to lower property values, this will provide strong evidence that crime has a downward pull on economic activity.

Heterogeneous Effects

We recognize that the impact of crime on economic activity may be heterogeneous. First, the type of crime might matter. For property crimes, such as burglary and theft, commercial goods are frequently the target of such crimes; we would expect this to be a primary concern for many retail business owners, but perhaps not as much for corporate business establishments. Violent crimes (such as robbery, homicide, and assault), on the other hand, occur less frequently and more idiosyncratically. Therefore, they might play less of a role in the decision of a property owner, business, or consumer to operate in or frequent a neighborhood. However, violent crimes can often be more publicized and severe, which can deter businesses, property purchasers, and consumers. Finally, public order crimes (such as loitering or disorderly conduct) might be less severe than the other two crime categories, but occur more often. These crimes could, in large numbers, negatively influence the local business environment, particularly retail establishments.

Second, we might expect that property values in neighborhoods that have other appealing characteristics, such as higher average incomes, will be affected differently than less endowed neighborhoods (i.e., those with lower average incomes). For example, relatively higher income neighborhoods might be able to withstand higher crime rates as business owners will still find those neighborhoods appealing due to sustained purchasing power. On the other hand, property values in high-income neighborhoods with increasing crime may have “farther to fall,” such that any change in crime is more of a shock to the status quo (i.e., not already capitalized into real estate prices). Finally, the type of commercial activity can mediate the effect of crime. For example, retail establishments (versus office buildings) might have fewer organized mechanisms for crime control and generate more pedestrian traffic, both of which provide more opportunity for crime.

3. REVIEW OF EMPIRICAL LITERATURE

There are two threads of research that are directly relevant to our analysis. First, there exists an important and established body of work that looks at the impact of crime on residential property values. Second, there is a growing body of literature that looks at the relationship between crime and business activity or economic growth. Here, we briefly review the former and, since it pertains more directly to our current analysis, provide more detail on the latter.

Crime and Residential Property Values

Studies on crime and residential property values investigate the role that crime plays in neighborhood decline and/or to identify the value that households place on crime control. The research generally finds that crime is associated with declines in residential property values, but the magnitude and significance of the effect differs by type of crime. Perhaps the most widely cited early paper on this topic was written by Richard Thaler (1978). Thaler estimated a hedonic price model to determine the effect of property crime on residential property values. Using data from Rochester, New York, Thaler found that large increases in property crime—approximately one standard deviation—are associated with a decrease in the price of about $430 per house. Hellman and Naroff (1979) found similar results, and Rizzo (1979) also found a negative effect, albeit smaller in magnitude. Buck, Hakim, and Spiegel (1991) looked at the location of casinos and the resulting increases in crime in Atlantic City to measure crime's impact on residential property values. Looking at 15 years of data in 64 Atlantic City area communities, they found that all crime types, except larceny, depress property values. Gibbons (2004) found that property crimes, except burglaries, have a significant and negative impact on residential prices in London. In a related paper using data from Atlantic City again, Buck, Hakim, and Spiegel (1993) find that increased spending on police clearly increases property values.

Taylor (1995) examined the effects of changing crime rates in Baltimore in the 1970s on property values and the decision to move. He found that decreases in assault and murder were associated with unexpected increases in housing value (unexpected is defined as being significantly different in the housing value change than comparable neighborhoods). Lynch and Rasmussen (2001) also found a negative relationship between violent crime and property values, but, surprisingly, they showed that the number of property crimes has a positive and significant impact on price. They suggested that this was due to the fact that better neighborhoods are more likely to have residents that report more petty crimes.

More recent papers have provided stronger evidence that crime has an impact on property values and the likelihood that people will want to live in a neighborhood. Linden and Rockoff (2008) investigate the relationship between the location of a registered sex offender and surrounding property values using data in North Carolina. They find that houses within one-tenth of a mile of such an offender fall in value by 4 percent. Carroll and Eger (2006) find in Milwaukee that brownfields and crime depress local property values, but Tax Increment Financing programs mitigate a lot of those negative effects. Schwartz et al. (2003) rely on rich microdata on properties in New York City and consider crime among several factors to explain the city's mid-1990s resurgence. They find that crime is an important, albeit incomplete, predictor of property value appreciation (housing investments appeared to play an important role, especially in poorer communities). Finally, Ihlanfeldt and Mayock (2010) improve upon previous analyses by constructing models to control for the endogeneity of crime; the authors still find that aggravated assault and robbery crimes reduce property values, by between 0.1 and 0.3 percent for every 1 percent increase in crimes per acre.

Crime and Economic Activity

Another area of research focuses on the relationship between crime and economic activity. The vast majority of this work looks at the effect of economic activity on crime, rather than vice versa—the focus of this paper. For example, there are many studies on the effect of unemployment on crime (for surveys of this literature, see Chiricos, 1987; see also Cantor and Land, 1985; Paternoster and Bushway, 2001; Raphael and Winter-Ebmer, 2001; Gould, Weinberg, and Mustard, 2002; Lin, 2008). Although there are some conflicting findings among these studies, the general consensus is that unemployment leads to increased property crime (violent crime is less clearly affected by increased unemployment).

More relevant for this paper is the smaller body of work that examines the effect of crime on business activity. The earliest paper that is commonly cited on this topic is a qualitative study conducted by Fisher (1991) among a group of small businesses in Columbus, Ohio. The author sent surveys to 102 businesses (42 percent response rate), focusing on the prevalence and type of crime victimization and their level of fear of crime and perceived disorder. Fisher finds that 94 percent of businesses report being victims of crime during a three-year span, with vandalism, vehicle theft, and burglary being the most common types of crime against these businesses. The costs to these businesses are not trivial—an average of $3,000 in property was reported lost to crime over a three-year span. Accordingly, business owners report that crime influences business decisions, such as whether to move or close down. Hollinger (1997) conducted a large survey of major retail chains in the U.S. and Canada. He finds that the two most important crimes for businesses are shoplifting and theft by employees. Hollinger also reports results from surveys in nonretail settings, where kickbacks and bribery, securities theft and fraud, and embezzlement are most disruptive to business operations. DiLonardo (1997) tests for the financial cost of shoplifting in retail stores. His method was to track stolen items through the ordering-to-replacement process to determine the true cost of the individual good to the store. He estimates that (assuming particular prices and quantities) for every coat stolen, 20 additional coats need to be sold to compensate for the loss. This is a valuable insight into the relatively sizeable costs of a particular crime (shoplifting) for retail businesses.

Hamermesh (1999) examines the extent to which neighborhood crime affects employees' sense of safety, and how they react in terms of employment preferences. He tests whether employees' preferences to work in the evenings are related to the likelihood of being victimized during those hours. Hamermesh found no evidence that the secular decline in the prevalence of evening and night work or the fact that working in evenings and nights is less common in larger metropolitan statistical areas has anything to do with crime. Levi (2001) used surveys of businesses in Great Britain to study the rates of victimization of these businesses. He finds that nearly 60 percent of the businesses surveyed had been victims of crime, with the most common types of crime being burglary, property damage, robbery, fraud, and assault. Furthermore, businesses in lower income areas are more likely to be victims of crime. Establishments such as hotels and restaurants, which are more commonly located in the central city, are those most frequently victimized by crime. Levi did find (somewhat counter to Hamermesh, 1999) that businesses reschedule staff hours to allow them to avoid dangerous situations if crime and violence become particularly common.

In a widely cited recent work on crime and neighborhood business activity, Greenbaum and Tita (2004) investigated whether surges in violence affect business establishment and employment growth. Using longitudinal, neighborhood-level homicide data in five cities, they determine that violence surges discourage new entrepreneurs in these areas and also push businesses out, resulting in reduced employment. In terms of industry type, homicide surges have the largest impact on slowing the creation of new retail and personal service businesses.

Bowes (2007) explicitly examined both the effect that crime has on business activity and the effect that diminished economic growth has on crime. He began with two hypotheses that shape a simultaneous, two-stage model of retail development and crime—that crime discourages retail activity, and that retail attracts crime. Using data on crime and retail in 206 census tracts in Atlanta from 1991 to 1994, Bowes finds strong support for each of these seemingly conflicting hypotheses. Bowes suggests that the efforts to revitalize downtowns should be accompanied with extra crime control capacity, given the propensity for retail development to attract crime. Rosenthal and Ross (2010) explicitly acknowledge this endogeneity in their analysis of violent crime and location of business activity and entrepreneurship in cities. They find that retail, wholesale, and restaurant activities are disproportionately located in high-crime areas (violent and motor-vehicle theft specifically). The authors determine that the pattern could be due to the fact that crime is attracted to these industries or the fact that businesses in other industries outbid those in these industries for safer locations.

Generally, we can conclude from these previous studies that crime has a downward pull on residential property values, but the effect on commercial property values is unclear. The small number of studies on the effect of crime on business activity suggests that businesses do incur nontrivial costs as a result of crime, but it is not particularly clear how profoundly these costs impact their willingness to locate in one neighborhood over another. The evidence also highlights the importance of recognizing a simultaneous relationship between crime and business activity. That is, at the same time that crime can depress business activity, business activity can attract more crime.

4. DATA AND METHODOLOGY

Data

To test for the impact of crime on commercial property values we combine three rich data sets. First, we use point-level crime data from the New York City Police Department. This data set contains information on the precise location, year, and type of crime for all reported incidents in New York City between 2004 and 2010. We categorize each reported crime into three types: property (i.e., burglary, arson, motor vehicle theft), violent (i.e., murder, robbery, assault), and public order (i.e., loitering, disorderly conduct, harassment) crimes (see a complete list of crime classifications in Appendix A). Second, we use data from the New York City Department of Finance on commercial property transactions and assessed values (AVs) for the same time period, 2004 through 2010 (all adjusted to 2010 dollars). This data set contains the universe of commercial properties in New York City, for which we obtain actual tentative AVs (i.e., those reported before the assessor has made any adjustments based on appeals). It also contains all commercial property sales (which constitute a subset of the universe of all commercial properties), including their location and amount. Finally, we include property characteristics from PLUTO, a data set created by the New York City Department of City Planning, for every property in New York City in 2009. For information on neighborhood demographic characteristics, we rely on data from the 2000 U.S. Census.

Since there are limitations to relying solely on either transaction-based or assessor-based property values, we run our analyses using both measures. While arms-length property sales represent actual willingness-to-pay in the market (which is an informative way to measure the value of the property's commercial activity), the sample of properties that transact may not be representative of the broader commercial building stock (and the economic activity housed within it). On the other hand, while AVs are available for the universe of commercial properties, they are not as responsive to market expectations and tend to change more slowly (Fisher et al., 2003). In the case of New York City, AVs are derived from calculations of the building's income (i.e., rents); however, rents are notoriously sticky (especially commercial ones, which tend to be bound by longer leases) (Mooradian and Yang, 2000; Genesove, 2003). Therefore, while AVs are a reasonable proxy for rents, they will not respond as quickly to market conditions, including crime increases

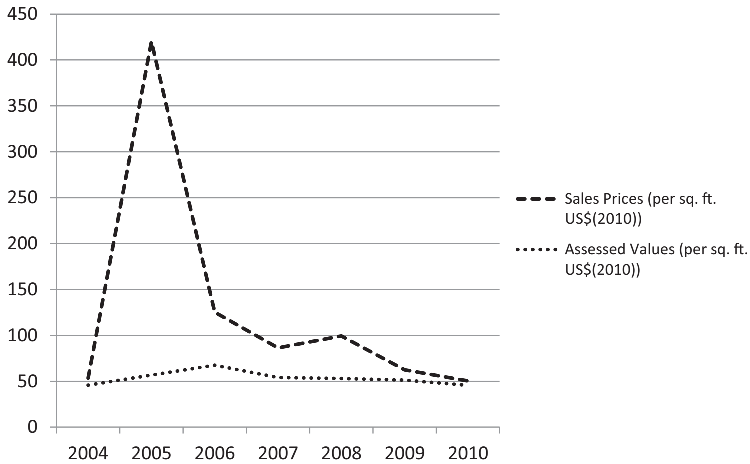

FIGURE 2: Sales Prices and Assessed Values

or decreases.[1] The relative stability of AVs is borne out in the data: although sales prices and AVs are both generally declining over the study period, the sales data exhibit much more volatility (see Figure 2).

To better discern whether or not the sales-based sample is significantly different than the AV-based sample, along observable characteristics, we run comparative statistics across the two. These are displayed in Table 1.[2] We see that most building characteristics are similar across the two samples, with the exception of building size, property classifications, and time since an alteration. Price ($386 per square foot compared to $53 per square foot of assessed value) and square footage are larger and the year of the last alteration is more recent for properties that transact, compared to the broader universe of assessed commercial parcels. In addition, properties that transact also tend to overrepresent retail and office properties (relative to other properties classified as industrial or mixed use). The sales sample also displays more variation over time; in general the characteristics of the bigger AV sample are stable across the study period (these annual statistics are not shown). The average crime counts across the study period are also slightly higher for the AV sample, but both samples display year-on-year changes that are quite variable. We control for all of these variables in the regression analyses that follow.

[1]Ideally, we would like to have actual rents, but these are unavailable for our comprehensive sample. Instead, we make the reasonable assumption that AVs will track rents, since the property assessment is made annually based on various calculations of the property's income (either reported or imputed from comparable rent rolls). The alignment of AVs and commercial rents will be least accurate among mixed use properties, which rely on both residential and commercial incomes. In our sample, these properties are primarily comprised of ground-floor retail/commercial, which constitutes a substantial share of the overall income and should therefore track reasonably well with the property's overall AV. For more information on how property assessments are made in NYC, please refer to http://www1.nyc.gov/site/finance/taxes/property-assessments.page.

[2]We have access to fewer property characteristics for the AV sample. However, based on the sales sample, the omitted variables are highly correlated with those included in the AV analysis and should therefore be controlled for in the regression analyses.

TABLE 1: Descriptive Statistics, Property Sales, and Assessed Values

	Sales			Assessed Values		
Variable	*N*	Mean	Std. Dev.	*N*	Mean	Std. Dev.
Price (AV) per sq. ft. US$(2010)	10,244	384	452	634,906	53	1110
Building sq. ft.	10,244	37990	140388	634,906	18777	85945
# Buildings on lot	10,244	1.17	0.70	634,906	1.07	0.50
# Floors in building	10,244	3.32	6.26	634,906	2.96	3.20
Lot frontage	10,244	79.95	95.78	634,906	109.64	79.15
Lot depth	10,244	120.73	86.91	634,906	61.21	86.91
Building age	10,244	73.69	144.00	634,906	75.60	24.64
Year altered (1st)	10,244	2006	11	146,818	1990	13
Year altered (2nd)	10,244	2010	4	21,118	1999	9
Building FAR	10,244	3.28	19.70			
Easement	10,244	0.02	0.14			
# Residential units	10,244	0.56	8.17	634,906	5.07	42.68
Basement (y/n)	10,244	0.00	–			
Irregular lot (y/n)	10,244	0.42	–			
Waterfront location (y/n)	10,244	0.00	–			
Corner location (y/n)	10,244	0.31	–			
Through lot (y/n)	10,244	0.02	–			
Assembled lot (y/n)	10,244	0.00	–			
Interior lot (y/n)	10,244	0.00	–			
Ownership status	10,244	0.98	–			
Retail class (y/n)	10,244	0.55	–	634,906	0.29	0.45
Office class (y/n)	10,244	0.22	–	634,906	0.11	0.32
Violent crimes per blockface	10,244	2.07	3.15	634,906	2.84	31.50
Property crimes per blockface	10,244	9.99	24.71	634,906	10.08	69.61
Public order crimes per blockface	10,244	10.46	15.78	634,906	12.78	78.28
Total units per blockface	10,244	71.36	229.66	634,906	129.72	2340.13
Liquor lics per blockface	10,244	1.83	2.98	634,706	0.52	1.14
Stores per blockface	10,244	1.72	3.15	633,589	1.44	2.98
Vacant bldgs per blockface	10,244	0.68	2.67	633,589	0.48	1.56
Violent crimes per H-block	10,244	9.80	12.90	641,332	11.37	14.35
Property crimes per H-block	10,244	49.65	114.79	641,332	46.87	99.29
Public order crimes per H-block	10,244	51.85	67.72	641,332	59.73	76.08
Total units per H-block	10,244	326.85	896.51	641,314	664.23	1452.82
Liquor lics per H-block	10,244	0.41	0.99	641,332	2.34	3.44
Stores per H-block	10,244	6.23	8.93	641,314	5.84	8.72
Vacant bldgs per H-block	10,244	2.91	5.57	641,314	2.58	4.46
Violent crimes per 1/4-mile ring	10,099	124.27	111.17			
Property crimes per 1/4-mile ring	10,099	571.98	819.43			
Public order crimes per 1/4-mile ring	10,099	657.35	585.52			
Chg in employ. rate (tract)	10,155	0.01	3.29	638,402	0.02	2.31
Total crime rate (precinct)	10,243	0.07	0.03	641,535	0.06	0.03

Empirical Strategy

We run regressions on two dependent variables. First, we use the real commercial sales price per square foot, and we use the natural logarithm to better fit the nonlinear nature of the data. As discussed above, this measure of commercial activity is comprehensive in that the price should capture any locational amenity (and disamenity) for that property. Second, we use actual tentative assessed values (adjusted to real dollars) per square foot, and, again, take the natural logarithm. The independent variable of interest is crime and we divide this into three types: property, violent, and public order.

Geographies of Crime

We sum up the total number of crimes, by type, for very localized areas surrounding the property. We run separate estimations for three levels of geography, which are progressively larger. First, we count the number of crimes for every blockface in New York City, and assign a blockface crime count to each property. The blockface is comprised of the two sides of a street that make up a city block. This differs from a census block, which would be the four street segments that you would walk along if you took a "walk around the block." In the blockface, each side of the street is included in the same unit of analysis. We believe the blockface captures the most spatially immediate impact of crime on property values and any effect should be more intense in this context. Second, we count the number of crimes on every "H-block" in New York City, and assign an H-block crime count to each property sale or assessed value. An H-block is an H-formation of adjacent city blockfaces.[3] Finally, we count the number of crimes within a quarter-mile radius of the property, and assign a ring crime count to each property sale or assessed value.[4]

We provide two illustrations of the various geographies that we employ in this paper. First, Figure 1 provides a graphical depiction of the blockface, H-block, quarter-mile buffer, half-mile buffer, and census tract boundaries for a neighborhood with a relatively consistent grid pattern. The blockface takes up one street segment around the parcel, and the H-block takes up seven street segments (note that not all street segments are equal length, in this example and across the city). The quarter-mile buffer includes roughly 45 street segments, and the half-mile includes over 175 street segments. Census tracts vary in size across the city, but in this neighborhood they are typically between 10 to 15 street segments.

Our goal is not to identify a single geography for crime but rather to test for any effect across a range of geographies, and observe whether or not effects dissipate over space. We begin with the blockface because it allows us to take the most advantage of the point-specific crime and property data we have at our disposal. The most well-known research to utilize this level of geography is from the Project on Human Development in Chicago Neighborhoods (PHDCN) (Sampson, 2012). But there is additional support from the criminology literature for using this level of geography as well. A widely cited piece by Ralph Taylor notes that "in many urban residential settings, residents experience markedly different safety when they move beyond their immediate block" (Taylor, 1997, p. 117). The H-block is slightly less restrictive, in that it allows us to identify the influence of crime across several adjacent street segments still within relative proximity of the parcel. The even larger quarter-mile buffer is similar to the ring-methodologies used extensively in studies of crime in urban planning (Loukaitou-Sideris and Sideris, 2009;

[3]In areas of the city with diagonal streets and other deviations from the classic grid street pattern displayed in Figure 2, the number of adjacent blockfaces may not be exactly five—the exact number may be larger or smaller—and about 95 percent of H-blocks consist of between four and nine blockfaces. This suggests a limitation with the H-block measure: some sales are linked to more adjacent blockfaces than others, and those sales will have inflated crime numbers. However, since we also control for H-block density, this bias should be minimized.

[4]We do not conduct regressions of assessed values on ring-based crime counts, due to the burden of calculation. We do replicate the ring-based sales analyses for larger half-mile rings, and the results are consistent, albeit smaller in magnitude (which is in line with the overall pattern of the presented results). These results are available from the authors upon request.

Joh, Nguyen, and Boarnet, 2012), urban economics (Bowes and Ihlanfeldt, 2001), and criminology (Weisburd, Groff, and Yang, 2013). This buffer allows us to observe a farther-reaching, but still walkable, geography of crime. We assume that the effect of crime on any property is not necessarily limited to those crimes on its host blockface, but also the crimes on the blocks surrounding it. Specifically, in order to visit a particular commercial establishment, one passes through several adjacent blocks and this larger setting is important in terms of valuing the commercial service and the property where it is located.

Considered in another way, Appendix B displays the annual number of violent, property, and public order crimes at five levels of geography employed in our analysis—blockface, H-block, quarter-mile, census tract, and precinct. The differentials are relatively consistent across crime type. H-blocks have roughly five times as many crimes as blockfaces; quarter-mile rings have another 12 times as many crimes as H-blocks. Census tracts are, on average, situated between H-blocks and quarter-mile rings—quarter-mile rings have about 2.5 times as many crimes as census tracts. Precincts are the largest of all; they have about 10 times as many crimes as the quarter-mile rings.

Since the amount of crime for any of these three geographies may be driven by the area's population density (for example, more densely populated neighborhoods create more opportunity for crime), we also control for blockface, H-block, and ring population densities by including in the regression model the total number of residential and commercial units in that particular geography in that year. Ideally, we would like to have population or pedestrian counts, but neither is available at these precise geographies or at annual intervals.[5]

Estimation

We rely on hedonic regression analysis to estimate the effect of crime on commercial property sales and assessed values.[6] The intuition is that crime is one of a number of locational characteristics that can influence the price of a nearby commercial property. We present the model using blockface crime aggregates (which will be replicated using H-block and ring crime aggregates) and this regression takes the following form:

$$LnPrice_{i,b,p,t} = \beta Crime_{b,t} + \gamma Density_{b,t} + \delta X_{i,b,t} + P_p + T_t + \varepsilon_{i,t}. \tag{1}$$

In this equation, *LnPrice* is the natural logarithm of the real price (or assessed value) per square foot for commercial property i on blockface b in precinct p and in year t; *Crime* is the total number of crimes (either violent, property or public order) on blockface b in

[5]We opt to measure crimes as a count variable and control for residential and commercial density, rather than measure crime as a rate. At a level of geography as small as the blockface, population does not vary as much as it does between larger areas—therefore most variation should be accurately captured by crime numbers. Furthermore, population measurement error is a bigger problem when the geographic area is small, and we wanted to keep this separate from the crime estimate. Lastly, crime rates at these small geographies take on very small values, making the interpretation of the coefficients less immediately meaningful. When we use precinct-level crime in our instrumental variables strategy, we express that variable as a rate, given New York City's precincts have over 100,000 people on average (minimizing the presence of measurement error).

[6]We rely on a hedonic model rather than constructing a repeat-sales index (which has the merits of mitigating against omitted variable bias), because we do not have enough repeat-sales at fine geographies to populate the model. We instead assume that the comprehensive collection of property and neighborhood characteristics do a good job at controlling for time-invariant differences across properties that may be correlated with price and/or crimes.

year t;[7] *Density* is the total number of units on blockface b in year t; and X is a vector of property characteristics for property i on blockface b in year t. The property characteristics control for a range of locational and structural features of the property and lot, including the number of buildings on the lot, number of floors, size of the lot, building age, year altered (if any), maximum buildable space, property classification (i.e., retail, office or other), number of easements, unit composition, ownership status (i.e., wholly private or some other public or quasi-public status), and any irregular structural characteristics. These hedonics are consistent with (and mostly more comprehensive than) those used in other hedonic analyses of commercial real estate (Mills, 1992; Quigg, 1993; Fisher et al., 2003; Debrezion, Pels, and Rietveld, 2007; Fuerst and McAllister, 2011).[8] In this vector, we also include covariates at the blockface level that (i) are correlated with the likelihood of a property sale and the incidence of crime in the surrounding area and that (ii) change over time (specifically, vacant buildings, stores, and active liquor licenses). Finally, we include police precinct fixed effects (P_{p}) to control for unobserved heterogeneity across neighborhoods (and crime-reporting districts) and year dummies (T_{t}) to control for more macro-level changes over time that are correlated with changes in crime and commercial property values.[9,10] The models using H-block and ring aggregates are identical to the blockface model, except for the crime and other locational covariates that are aggregated up to the H-block and ring levels instead of the blockface. Descriptive statistics for all variables are included in Table 1.

Despite these extensive controls, this model is unable to fully control for the simultaneous relationship between crime and property values. Specifically, while we intend to identify the impact of crime on property values, we recognize that property values (and economic activity more broadly) could simultaneously drive crime (Ihlanfeldt and Mayock, 2010). First, locations with greater commercial activity and higher prices are also more likely to attract more crime due to more pedestrian traffic and more lucrative property crime targets. If this were true, then our OLS estimates would be biased upward. On the other hand, locations with higher property values may contain more vigilant residents, consumers or security personnel such that crime is relatively lower; in this case our OLS estimates would be biased down. In sum, the bias is ambiguous, but it needs to be addressed in our crime estimates.

To address this endogeneity, we instrument for crime on the blockface (and, when relevant, the H-block and in the proximate quarter-mile ring) in two ways: using *change*

[7]We replicate the models using crime lagged one year and the results are substantively the same. We do not have enough data points to lag the crime counts by longer periods without significantly compromising the sample size. We do, however, control for earlier crime rates, at the precinct level, and the results are substantively the same to those presented in the paper. Ultimately, we opt for the more parsimonious model, with the most observations (i.e., contemporaneous crime counts without earlier precinct crime rates).

[8]We do not have information on the class of commercial property, but instead rely on the type of property (i.e., retail or office) and year built and altered as proxies for property quality.

[9]We also run OLS models with ZIP Code dummies and precinct-year fixed effects (to allow any unobserved precinct heterogeneity vary over time) and the results are substantively the same. We opt against this specification, because in the 2SLS models we use precinct-level crime as an instrument and we cannot include this variable, which varies across time, in the presence of precinct-year fixed effects.

[10]We also run models where the standard errors are clustered by blockface/H-block, since multiple properties can be located on the same blockfaces/H-blocks. The clustered standard errors are marginally bigger than the robust ones and do not change the results substantively. We are not concerned, however, since there does not appear to be a large degree of spatial correlation or heteroskedasticity (based on a high correspondence between the clustered and robust standard errors); the main results are unchanged. The results using clustered standard errors are available from the authors upon request.

in employment rates (at the census tract level for blockface and H-block analyses and at the ZIP Code-level for ring analyses) and precinct crime rates. We normalize the employment counts by dividing them by counts of total residential units in the corresponding geography, and then take the difference in employment rates between t and $t-1$. We opt for the unit-based proxy for population over census counts, as it is recorded annually (rather than interpolated for inter-centennial years). The tract-level employment data are from the U.S. Census Longitudinal Employer-Household Dynamics (LEHD) database (which we also use to construct the ZIP Code rates). As noted in Section III, there is a large body of research that confirms a positive relationship between crime and unemployment (for surveys of this literature, see Chiricos, 1987; see also Cantor and Land, 1985; Paternoster and Bushway, 2001; Raphael and Winter-Ebmer, 2001; Gould, Weinberg, and Mustard, 2002; Lin 2008;). This relationship is not entirely straightforward—property crime appears to be more affected than violent crime, and most of these studies use large geographies such as countries, states, and metropolitan areas. However, two studies (Ihlanfeldt, 2002; Ihlanfeldt, 2006) find that a dearth of young male employment opportunities at the neighborhood level lead to elevated crime rates in those neighborhoods. Thus, we assume that the essential theories that predict a strong relationship between unemployment and crime at the state and city/metropolitan area hold at the neighborhood or block level. We also posit that since local investors and businesses will likely search for labor outside of the immediate neighborhood, the census tract employment rate will not be correlated with changes in commercial property values over time. In addition, we theorize that buyers, renters and sellers of commercial property are not privy to information on how census tract employment numbers are changing annually, as the data we use are not widely published. This is borne out in the data, as the correlation between the commercial sales price and the change in employment rate is very small (0.01); and the correlation between AV and change in employment rate is even smaller at −0.0002.

To take advantage of additional exogenous variation, we also use precinct total crime rates as an instrument.[11] The intuition here is that precinct crime rates will capture some overall reporting patterns that will be correlated with blockface (or H-block or ring) crime counts (of all types). We maintain that these precinct rates are exogenous to commercial property values since the estimation model also includes precinct fixed effects; in other words, we are essentially comparing properties *within* individual precincts, over time. Therefore, controlling for the other property and geography-specific covariates in the model, precinct-level crime rates should not be correlated with within-precinct variation of commercial values over time and thus should not present a credible threat to exogeneity. The correlations between sales price and precinct crime rate and between assessed values and precinct crime rate are very small (0.02 and 0.003, respectively).

5. RESULTS

Baseline Regressions

In Tables 2 and 3, we provide the results from the OLS regressions, for blockface, H-block and ring models, and for regressions using both property sales and AVs. These specifications include precinct fixed effects and year dummy variables, as well as the full

[11]We also run models with precinct total crime lagged five years as an instrument to guard against simultaneity. The results are largely consistent with the contemporaneous version of precinct total crime, but the instrument does not perform as well and the second-stage coefficients are suspiciously inflated. Therefore, we opt for the contemporaneous version, even though the lagged version may be more theoretically conservative.

TABLE 2: OLS Models, with Controls (Dependent Variable: Sales Prices)

	Blockface			H-block			1/4-mile Ring		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Ln(*PriceSF*) Violent	Ln(*PriceSF*) Property	Ln(*PriceSF*) Public Order	Ln(*PriceSF*) Violent	Ln(*PriceSF*) Property	Ln(*PriceSF*) Public Order	Ln(*PriceSF*) Violent	Ln(*PriceSF*) Property	Ln(*PriceSF*) Public Order
# Crimes	0.008**	0.002***	0.001	−0.0001	0.0002**	0.0002	0.00001	0.0001	0.0001
	(0.00400)	(0.00050)	(0.00080)	(0.00100)	(0.00010)	(0.00020)	(0.00020)	(0.00002)	(0.00003)
# Units per BF (100s)$^{\wedge}$	−0.00002	−0.00002	−0.00002	−0.001	−0.001	−0.001	−0.000003	−0.00001	−0.00001
	(0.00010)	(0.00010)	(0.00010)	(0.00154)	(0.00149)	(0.00153)	(0.00001)	(0.00001)	(0.00001)
# Buildings on lot	−0.0755***	−0.0754***	−0.0758***	−0.0772***	−0.0766***	−0.0769***	−0.0698***	−0.0689***	−0.0691***
	(0.0179)	(0.0178)	(0.0179)	(0.0178)	(0.0177)	(0.0178)	(0.0176)	(0.0175)	(0.0175)
# Floors in building	−0.0463***	−0.0464***	−0.0463***	−0.0462***	−0.0461***	−0.0462***	−0.0466***	−0.0473***	−0.0470***
	(0.00362)	(0.00364)	(0.00362)	(0.00362)	(0.00362)	(0.00362)	(0.00386)	(0.00388)	(0.00387)
Lot frontage	−0.0006***	−0.0006***	−0.0006***	−0.0006***	−0.0006***	−0.0006***	−0.0006***	−0.0006***	−0.0006***
	(0.000150)	(0.000151)	(0.000150)	(0.000149)	(0.000150)	(0.000149)	(0.000153)	(0.000152)	(0.000152)
Lot depth	−0.000223	−0.000235	−0.000221	−0.000222	−0.000231	−0.000223	−0.000167	−0.000169	−0.000159
	(0.000191)	(0.000192)	(0.000191)	(0.000190)	(0.000191)	(0.000190)	(0.000197)	(0.000196)	(0.000196)
Building Age	0.000142*	0.000141*	0.000140*	0.000137*	0.000138*	0.000138*	0.000101	0.000100	0.000102
	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)
Year Altered (1st)	0.000516	0.000450	0.000514	0.000662	0.000669	0.000677	0.000658	0.000655	0.000649
	(0.000935)	(0.000935)	(0.000936)	(0.000934)	(0.000931)	(0.000933)	(0.000942)	(0.000939)	(0.000942)
Year Altered (2nd)	−0.000594	−0.000384	−0.000691	−0.000616	−0.000371	−0.000611	0.0001	0.000733	0.000150
	(0.00262)	(0.00257)	(0.00262)	(0.00261)	(0.00259)	(0.00260)	(0.00253)	(0.00252)	(0.00253)
Building FAR	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***
	(0.000998)	(0.00101)	(0.00100)	(0.000973)	(0.000976)	(0.000974)	(0.00103)	(0.00102)	(0.00102)
Office property	0.233***	0.236***	0.235***	0.232***	0.231***	0.230***	0.238***	0.232***	0.234***
	(0.0326)	(0.0325)	(0.0326)	(0.0327)	(0.0326)	(0.0327)	(0.0332)	(0.0332)	(0.0332)
Retail property	0.369***	0.370***	0.370***	0.375***	0.374***	0.373***	0.387***	0.384***	0.382***
	(0.0268)	(0.0267)	(0.0269)	(0.0267)	(0.0266)	(0.0267)	(0.0273)	(0.0272)	(0.0273)
Easement	−0.0490	−0.0480	−0.0473	−0.0494	−0.0490	−0.0491	−0.0795	−0.0838	−0.0808
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.108)	(0.108)	(0.108)
# Residential units	−0.00157	−0.00154	−0.00160	−0.00156	−0.00159	−0.00158	−0.00164	−0.00159	−0.00162
	(0.00141)	(0.00141)	(0.00141)	(0.00141)	(0.00141)	(0.00141)	(0.00132)	(0.00132)	(0.00132)
Basement	−0.646**	−0.651**	−0.654**	−0.625**	−0.625**	−0.622**	−0.402*	−0.392*	−0.394*

(Continued)

TABLE 2: Continued

	Blockface			H-block			1/4-mile Ring		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Ln(*PriceSF*) Violent	Ln(*PriceSF*) Property	Ln(*PriceSF*) Public Order	Ln(*PriceSF*) Violent	Ln(*PriceSF*) Property	Ln(*PriceSF*) Public Order	Ln(*PriceSF*) Violent	Ln(*PriceSF*) Property	Ln(*PriceSF*) Public Order
	(0.287)	(0.287)	(0.289)	(0.281)	(0.281)	(0.281)	(0.231)	(0.229)	(0.229)
Irregular lot	0.0644***	0.0644***	0.0648***	0.0609***	0.0615***	0.0616***	0.0597***	0.0590***	0.0600***
	(0.0211)	(0.0211)	(0.0212)	(0.0211)	(0.0211)	(0.0211)	(0.0215)	(0.0215)	(0.0215)
Waterfront location	−0.304	−0.305	−0.307	−0.334	−0.325	−0.328	−0.662**	−0.673**	−0.658**
	(0.302)	(0.302)	(0.302)	(0.304)	(0.304)	(0.304)	(0.284)	(0.284)	(0.283)
Corner location	−0.0188	−0.0174	−0.0199	−0.0265	−0.0245	−0.0261	−0.0170	−0.0177	−0.0175
	(0.0218)	(0.0218)	(0.0218)	(0.0217)	(0.0217)	(0.0217)	(0.0220)	(0.0220)	(0.0220)
Through lot	−0.134**	−0.131**	−0.135**	−0.141**	−0.140**	−0.140**	−0.125**	−0.127**	−0.126**
	(0.0627)	(0.0628)	(0.0627)	(0.0631)	(0.0630)	(0.0631)	(0.0636)	(0.0636)	(0.0636)
Assembled lot	−0.00543	−0.00265	−0.00845	−0.0216	−0.0181	−0.0190	0.00318	0.00525	0.00251
	(0.216)	(0.217)	(0.216)	(0.216)	(0.216)	(0.215)	(0.216)	(0.216)	(0.216)
Interior lot	−0.0664	−0.0643	−0.0702	−0.0431	−0.0427	−0.0416	−0.0315	−0.0283	−0.0283
	(0.203)	(0.199)	(0.202)	(0.198)	(0.198)	(0.198)	(0.191)	(0.189)	(0.195)
Ownership status	−0.129**	−0.131**	−0.127**	−0.126**	−0.128**	−0.126**	−0.179***	−0.186***	−0.182***
	(0.0612)	(0.0612)	(0.0613)	(0.0610)	(0.0609)	(0.0610)	(0.0587)	(0.0585)	(0.0586)
Liquor lics per BF$^{\wedge}$	0.00952**	0.0104**	0.00982**	0.000834	0.000835	0.000177	0.0105	0.00871	0.00900
	(0.00451)	(0.00446)	(0.00453)	(0.00998)	(0.00993)	(0.00999)	(0.0105)	(0.0105)	(0.0105)
Stores per BF$^{\wedge}$	0.0154***	0.0147***	0.0161***	0.00765***	0.00721***	0.00744***	0.0165***	0.0162***	0.0162***
	(0.00311)	(0.00304)	(0.00310)	(0.00114)	(0.00112)	(0.00113)	(0.00318)	(0.00318)	(0.00318)
Vacant bldgs per BF$^{\wedge}$	−0.00192	−0.00211	−0.00209	−0.00392*	−0.00393*	−0.00397*	−0.0222***	−0.0220***	−0.0224***
	(0.00468)	(0.00473)	(0.00472)	(0.00219)	(0.00219)	(0.00219)	(0.00675)	(0.00674)	(0.00675)
N	10,244	10,244	10,244	10,244	10,244	10,244	10,092	10,092	10,092
Adjusted R-squared	0.20	0.20	0.20	0.20	0.20	0.20	0.21	0.21	0.21

Notes: ^BF = blockface in results columns 1–3, H-block for columns 4–6, ring for columns 7–9; all models include precinct fixed effects and year dummies; All regressions use sales transaction data for 2004–2010; "ownership status" takes on the value of 1 for privately owned properties and 0 for other public or quasi-public properties; "Building FAR" is the built floor-area-ratio. Robust standard errors in parentheses; $^{*}P < 0.10$; $^{**}P < 0.05$; $^{***}P < 0.01$.

TABLE 3: OLS Models, with Controls (Dependent Variable: Assessed Values)

	Blockface			H-block		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Ln(*AVPSqft*) Violent	Ln(*AVPSqft*) Property	Ln(*AVPSqft*) Public Order	Ln(*AVPSqft*) Violent	Ln(*AVPSqft*) Property	Ln(*AVPSqft*) Public Order
# Crimes	0.0001	0.0009***	0.0004***	−0.0002***	0.0002***	0.00001
	(0.000288)	(0.0001)	(0.0001)	(0.0001)	(0.00001)	(0.00002)
# Units per BF (100s)ˆ	0.000003	0.000001	0.000001	−0.000004***	−0.00001***	−0.00001***
	(0.000004)	(0.000004)	(0.000004)	(0.000001)	(0.000001)	(0.000001)
# Buildings on lot	−0.000868	−0.000435	−0.000784	−0.0133***	−0.0129***	−0.0132***
	(0.00229)	(0.00229)	(0.00229)	(0.00231)	(0.00231)	(0.00232)
# Floors in building	−0.0294***	−0.0294***	−0.0295***	−0.0281***	−0.0282***	−0.0281***
	(0.000477)	(0.000476)	(0.000477)	(0.000352)	(0.000353)	(0.000352)
Lot frontage	0.00108***	0.00108***	0.00108***	0.000972***	0.000969***	0.000972***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Lot depth	0.000137***	0.000131***	0.000137***	0.000141***	0.000137***	0.000141***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Building age	−0.00673***	−0.00674***	−0.00674***	−0.00683***	−0.00683***	−0.00684***
	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)
Year altered (1st)	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.000001)	(0.000001)	(0.000001)	(0.000001)	(0.000001)	(0.000001)
Year altered (2nd)	0.00001***	0.00001***	0.00001***	0.00001***	0.00001***	0.00001***
	(0.000002)	(0.000002)	(0.000002)	(0.000002)	(0.000002)	(0.000002)
Office property	1.190***	1.190***	1.190***	1.189***	1.188***	1.189***
	(0.00216)	(0.00215)	(0.00216)	(0.00211)	(0.00210)	(0.00211)
Retail property	1.004***	1.003***	1.004***	1.001***	1.001***	1.001***
	(0.00297)	(0.00297)	(0.00297)	(0.00274)	(0.00274)	(0.00274)
# Residential units	0.000221***	0.000223***	0.000221***	−1.79e-05	−7.33e-06	−1.63e-05
	(0.00010)	(0.00010)	(0.00010)	(0.00001)	(0.00001)	(0.00001)
Liquor lics per BFˆ	−0.00728***	−0.00734***	−0.00777***	−0.00382***	−0.00410***	−0.00396***
	(0.000779)	(0.000773)	(0.000779)	(0.000300)	(0.000298)	(0.000301)
Stores per BFˆ	0.0176***	0.0160***	0.0173***	0.00697***	0.00643***	0.00689***
	(0.000284)	(0.000289)	(0.000284)	(0.000101)	(0.00010)	(0.000100)
Vacant bldgs per BFˆ	−0.00720***	−0.00727***	−0.00724***	−0.00793***	−0.00789***	−0.00792***
	(0.000688)	(0.000689)	(0.000689)	(0.000270)	(0.000269)	(0.000269)
N	633,589	633,589	633,589	641,314	641,314	641,314
Adjusted *R*-squared	0.63	0.64	0.63	0.63	0.64	0.63

Notes: ˆBF = blockface in results columns 1–3, H-block for columns 4–6; all models include precinct fixed effects and year dummies; all regressions use AV data for 2004–2010. Robust standard errors in parentheses; *$P < 0.10$; **$P < 0.05$; ***$P < 0.01$.

set of property- and geography-specific control variables. We first highlight a few of the hedonic results. The covariates pertaining to the parcel's lot and structure dimensions (i.e., frontage, depth, number of floors, irregular shape, built floor-area-ratio) and the building's classification (i.e., office and retail, compared to other industrial or mixed classifications), ownership status and age (controlling for dates of recent, major alterations) are the strongest determinants of price. This is largely consistent with other hedonic analyses of commercial prices and rents (Mills, 1992; Quigg, 1993; Fisher et al., 2003).

Turning to the crime results, we see in Table 2 that the relationship between property values and crime on the blockface, regardless of type, is positive (and highly significant for violent and property crimes), meaning higher crime blockfaces have higher commercial property values. For the models using the H-block and the ring crime metrics, the crime coefficients not only decrease in magnitude, but are also largely insignificant. Therefore, the covariation between crime and property values, while it appears positive, is more intense within a smaller radius. For property crimes on the same blockface as a sale, the coefficient of 0.002 suggests that one additional property crime on a blockface is associated with a 0.2 percent increase in sales price.

In Table 3, we replicate the same models replacing the dependent variable with AV measures. As above, we include precinct fixed effects and year dummy variables. Again, the hedonics indicate that the parcel's lot and structure dimensions and the building's classification and age are the strongest determinants of price. Like the results from the sales sample, the coefficients on property crime are positive, significant and of a similar magnitude (for both the blockface and H-block results). Violent crime, however, is insignificant in the blockface models and significant and negative in the H-block models, and public order exhibits a significant positive coefficient in the blockface models (it is insignificant in the H-block regression). The AV-based models suggest that an additional property crime on the blockface reduces prices by about 0.1 percent, or \$0.05 per square foot (based on a mean square foot AV of \$53). Since the AV-based regressions rely on a much larger and inclusive sample, it is not entirely surprising that the results would differ. We also know that the AVs are less volatile over time, introducing less noise into our estimates (see Figure 2); this suggests that our AV-based estimates will also be more precise. Nevertheless, we assume that the OLS models are failing to control for the simultaneity between crime and commercial prices.

2SLS Regressions

Therefore, we turn to the 2SLS models, which attempt to mitigate any reverse causality that could be biasing the above results. We display the second stage results for the 2SLS models on the sales sample in Table 4, and, again, we show the results for the blockface, H-block, and quarter-mile ring models and for each crime type separately. We first note that our instruments perform satisfactorily. Following Ihlanfeldt and Mayock (2010), we rely on two indicators of instrument validity: the first stage F-statistic and the Sargan-Hansen test (these results are displayed in Appendix C for the sales models and Appendix D for the assessed value models). For all geographies and crime types, the F-statistic for the first stage regression is above 20 (most dramatically so for the ring models) and highly significant. The Sargan-Hansen tests also support the instruments' validity (with their low test values), with the exception of violent and public order crimes in the ring models, which produce statistically significant test results (i.e., we reject the null of instrument validity).[12]

[12]We run identical specifications with the change in employment rate calculated at the census tract level (as in the blockface and H-block models), and the second-stage results are nearly identical with lower

TABLE 4: Second-stage Models (Dependent Variable: Sales Prices)

	Blockface			H-block			1/4-mile Ring		
	(1) Ln(*PriceSqFt*)	(2) Ln(*PriceSqFt*)	(3) Ln(*PriceSqFt*)	(4) Ln(*PriceSqFt*)	(5) Ln(*PriceSqFt*)	(6) Ln(*PriceSqFt*)	(7) Ln(*PriceSqFt*)	(8) Ln(*PriceSqFt*)	(9) Ln(*PriceSqFt*)
VARIABLES	Violent	Property	Public Order	Violent	Property	Public Order	Violent	Property	Public Order
# Crimes	−0.213*	−0.028	−0.039	−0.088	−0.009	−0.017	−0.005**	−0.002**	−0.0002
	(0.116)	(0.0184)	(0.0217)	(0.0560)	(0.0078)	(0.0122)	(0.0021)	(0.0006)	(0.0006)
# Units per BF (100s)ˆ	0.000128	0.0001	0.000129	0.0104	0.00245	0.0103	0.00004**	0.00003**	0.00001
	(0.0001)	(0.0001)	(0.0001)	(0.00807)	(0.00492)	(0.00866)	(0.00002)	(0.00001)	(0.00003)
# Buildings on lot	−0.0949***	−0.0902***	−0.0884***	−0.106***	−0.103***	−0.109***	−0.0843***	−0.0980***	−0.0783***
	(0.0236)	(0.0224)	(0.0218)	(0.0294)	(0.0312)	(0.0334)	(0.0203)	(0.0244)	(0.0204)
# Floors in building	−0.0458***	−0.0444***	−0.0474***	−0.0437***	−0.0484***	−0.0454***	−0.0416***	−0.0407***	−0.0447***
	(0.00384)	(0.00508)	(0.00410)	(0.00459)	(0.00514)	(0.00470)	(0.00412)	(0.00540)	(0.00455)
Lot frontage	−0.000470**	−0.000198	−0.000288	−0.000386*	1.21e-05	−0.000175	−0.000707***	−0.000639***	−0.000569***
	(0.000186)	(0.000313)	(0.000249)	(0.000232)	(0.000549)	(0.000366)	(0.000174)	(0.000178)	(0.000162)
Lot depth	−0.000179	−0.00002	−0.000232	−0.000227	0.000140	−0.0001	−0.000323	−0.000144	−0.000202
	(0.000219)	(0.000266)	(0.000221)	(0.000253)	(0.000427)	(0.000319)	(0.000222)	(0.000216)	(0.000227)
Building age	0.00007	0.000102	0.00009	−0.00002	0.00007	0.00003	0.0001	0.0001	0.000104
	(0.0001)	(0.0001)	(0.0001)	(0.000132)	(0.000100)	(0.000114)	(0.000100)	(0.000100)	(0.000100)
Year altered (1st)	0.00101	0.00198	0.00124	−0.000376	0.000290	−0.00115	0.00113	0.000365	0.000746
	(0.00117)	(0.00149)	(0.00115)	(0.00162)	(0.00219)	(0.00204)	(0.00103)	(0.00152)	(0.000978)
Year altered (2nd)	−0.00141	−0.00438	0.00162	−0.00435	−0.0107	−0.000760	−0.00268	−0.0150*	−0.000992
	(0.00302)	(0.00672)	(0.00319)	(0.00497)	(0.0120)	(0.00476)	(0.00274)	(0.00876)	(0.00265)
Building FAR	−0.00217	−0.00004	−0.000316	−0.00339***	−0.00246**	−0.00162	−0.00350***	−0.00247**	−0.00339***
	(0.00134)	(0.00241)	(0.00213)	(0.00112)	(0.00113)	(0.00162)	(0.00123)	(0.00116)	(0.00113)
Office property	0.373***	0.258***	0.348***	0.427***	0.237***	0.398***	0.305***	0.332***	0.246***
	(0.0841)	(0.0405)	(0.0718)	(0.133)	(0.0439)	(0.127)	(0.0462)	(0.0555)	(0.0503)
Retail property	0.533***	0.440***	0.520***	0.586***	0.432***	0.594***	0.482***	0.494***	0.402***
	(0.0950)	(0.0546)	(0.0885)	(0.143)	(0.0632)	(0.163)	(0.0520)	(0.0529)	(0.0698)
Easement	−0.0282	−0.0525	−0.0718	−0.0635	−0.0755	−0.0809	−0.0525	−0.0347	−0.0676
	(0.107)	(0.113)	(0.108)	(0.118)	(0.123)	(0.119)	(0.107)	(0.120)	(0.106)
# Residential units	−0.00231	−0.00253	−0.00161	0.000181	−0.000435	−.000004	−0.00162	−0.00231	−0.00171
	(0.00167)	(0.00166)	(0.00140)	(0.00233)	(0.00201)	(0.00228)	(0.00135)	(0.00169)	(0.00139)
Basement	−0.659**	−0.573**	−0.373	−1.172**	−0.626**	−0.880**	−0.704**	−0.875**	−0.624**

(Continued)

TABLE 4: Continued

	Blockface			H-block			1/4-mile Ring		
	(1) Ln(*PriceSqFt*)	(2) Ln(*PriceSqFt*)	(3) Ln(*PriceSqFt*)	(4) Ln(*PriceSqFt*)	(5) Ln(*PriceSqFt*)	(6) Ln(*PriceSqFt*)	(7) Ln(*PriceSqFt*)	(8) Ln(*PriceSqFt*)	(9) Ln(*PriceSqFt*)
VARIABLES	Violent	Property	Public Order	Violent	Property	Public Order	Violent	Property	Public Order
	(0.291)	(0.291)	(0.300)	(0.514)	(0.298)	(0.369)	(0.294)	(0.353)	(0.292)
Irregular lot	0.0235	0.0364	−0.00235	0.0349	0.0390	−0.00718	0.0627***	0.0916***	0.0569***
	(0.0334)	(0.0306)	(0.0432)	(0.0337)	(0.0325)	(0.0569)	(0.0225)	(0.0297)	(0.0212)
Waterfront location	−0.893**	−0.729**	−0.902**	−1.132**	−0.905*	−1.091**	−0.899***	−0.534	−0.724**
	(0.377)	(0.345)	(0.378)	(0.527)	(0.466)	(0.533)	(0.325)	(0.383)	(0.309)
Corner location	−0.0879*	−0.0847*	−0.0686*	−0.0740*	−0.107	−0.0609	−0.0387	−0.0576*	−0.0263
	(0.0465)	(0.0495)	(0.0379)	(0.0443)	(0.0754)	(0.0413)	(0.0237)	(0.0302)	(0.0230)
Through lot	−0.241**	−0.259**	−0.245***	−0.266**	−0.191	−0.276*	−0.130**	−0.189**	−0.141**
	(0.0950)	(0.106)	(0.0928)	(0.124)	(0.131)	(0.146)	(0.0652)	(0.0880)	(0.0629)
Assembled lot	−0.258	−0.220	−0.222	−0.259	−0.175	−0.301	−0.0625	−0.118	−0.0449
	(0.256)	(0.264)	(0.249)	(0.285)	(0.283)	(0.315)	(0.218)	(0.249)	(0.217)
Interior lot	0.0708	−0.0131	0.242	0.0436	−0.0643	−0.212	0.137	−0.168	−0.145
	(0.205)	(0.225)	(0.276)	(0.205)	(0.227)	(0.269)	(0.285)	(0.193)	(0.160)
Ownership status	−0.000852	−0.0190	−0.0379	0.0611	−0.0137	−0.0352	−0.0269	0.0221	−0.141**
	(0.0977)	(0.0929)	(0.0799)	(0.143)	(0.119)	(0.105)	(0.0838)	(0.102)	(0.0648)
Liquor lics per BF^	0.0484**	0.0199**	0.0488**	0.0443	−0.000313	0.0697	0.0200	0.0408	0.00870
	(0.0212)	(0.00932)	(0.0215)	(0.0322)	(0.0206)	(0.0513)	(0.0135)	(0.0256)	(0.0242)
Stores per BF^	0.0537***	0.0530**	0.0426***	0.0337**	0.0257*	0.0287*	0.0259***	0.0331***	0.0187***
	(0.0205)	(0.0246)	(0.0148)	(0.0166)	(0.0153)	(0.0149)	(0.00496)	(0.00726)	(0.00482)
Vacant bldgs per BF^	−0.00340	0.000344	0.00231	−0.00408	−0.00337	0.00196	−0.0176**	−0.0204***	−0.0172**
	(0.00569)	(0.00472)	(0.00507)	(0.00285)	(0.00260)	(0.00490)	(0.00701)	(0.00732)	(0.00681)
N	10,155	10,155	10,155	10,155	10,155	10,155	10,047	10,047	10,047

Notes: ^BF = blockface in results columns 1–3, H-block for columns 4–6, ring for columns 7–9; all models include precinct fixed effects and year dummies; All regressions use sales transaction data for 2004–2010; "ownership status" takes on the value of 1 for privately owned properties and 0 for other public or quasi-public properties; "Building FAR" is the built floor-area-ratio. Robust standard errors in parentheses; *$P < 0.10$; **$P < 0.05$; ***$P < 0.01$.

Turning to the results from the second stage models in Table 4, we see that, overall, the signs on the crime coefficients become negative and increase in magnitude; however, there is very little statistical significance. As with the OLS estimates, the violent crime coefficient is bigger in magnitude than those for the other two crime types; however, it is insignificant (i.e., with a *P*-value bigger than 0.05) at smaller geographies (i.e., blockface and H-block). At larger spans (i.e., the quarter-mile ring), we see that each additional violent crime reduces prices by about 0.5 percent (or \$1.90 per square foot, based off of the mean sales price per square foot). While negative, the coefficients on property and public order crimes are also insignificant at smaller geographies; at larger ring-based geographies, the property and violent crime coefficients are both significant. These results indicate that an additional property crime within a quarter-mile decreases prices by about 0.2 percent (or just over \$0.75 per square foot), which is slightly smaller than the violent crime effect (where an additional violent crime reduces prices by 0.5 percent). Public order crime still exhibits no significant effect on prices.

We replicate the same models using the AV-based dependent variable. As above, the instruments perform well (see Appendix D). The first-stage *F*-statistics are highly significant (i.e., very large) and the Sargan-Hansen tests consistently produce low test statistics for both blockface and H-block models and for all types of crime; together these provide support for the instruments' validity. The second-stage results are consistent with those from the sales-based models (displayed in Table 5), but due to the larger sample, are estimated with more precision. The coefficient on violent crime is now negative and highly significant for both the blockface and H-block geographies. For the H-block results we note that the magnitude of the coefficient, while still negative, has increased, suggesting that the endogeneity of crime was indeed biasing the crime coefficient up (i.e., making it less negative). Here, prices drop by about 6 percent (or \$3.20 per square foot) with an additional violent crime on the blockface and about 1 percent (or just over \$0.50 per square foot) with an additional violent crime on the H-block. This effect is larger than that observed for both property and public order crimes. Such an effect seems large until we recall that the average blockface has 2.1 major violent crimes per year, meaning an additional violent crime is a very large (50 percent) jump. The price elasticity[13] is 0.18, meaning is that a 1 percent increase in violent crime is associated with a 0.18 percent decrease in assessed value. This estimate (and elasticities for other significant coefficients) is well-within the range of elasticities reported from studies examining the effect of crime on residential property values (Hellman and Naroff, 1979; Thaler, 1979; Gibbons, 2004; Ihlanfeldt and Mayock, 2010).

For the blockface aggregates, an additional property crime reduces prices by about 2 percent (or \$1.05 per square foot) and an additional public order crime results in a similar price drop. For the H-block measures, an additional property or public order crime reduces prices by about 0.4 percent (or just over \$0.20 per square foot). Therefore, both proximity and type of crime matter: the effect from an additional violent crime is more than two-times that from property or public order crimes and the effect is intensified at closer ranges. Both of these observations are supported by results out of the sales and AV samples.

Sargan-Hansen statistics (that do not lead us to reject the validity of the instruments). We use the ZIP Code-level measures, however, because conceptually they are more compelling, since the ZIP Code is a larger geography than the quarter-mile ring, whereas census tracts can be smaller than the ring span.

[13]Note that while our models are expressed in log-linear terms, we separately ran log-log models in order to estimate elasticities.

TABLE 5: Second-stage Models (Dependent Variable: Assessed Values)

	Blockface			H-block		
	(1) Ln(*AVPSqft*)	(2) Ln(*AVPSqft*)	(3) Ln(*AVPSqft*)	(4) Ln(*AVPSqft*)	(5) Ln(*AVPSqft*)	(6) Ln(*AVPSqft*)
Variables	Violent	Property	Public Order	Violent	Property	Public Order
# Crimes	−0.0592***	−0.0203**	−0.0172***	−0.0131***	−0.00399***	−0.00373***
	(0.0116)	(0.00974)	(0.00345)	(0.00247)	(0.00123)	(0.000725)
# Units per BF (100s)ˆ	0.00004***	0.00004**	0.0001***	0.00001***	0.00001**	0.00003***
	(0.00001)	(0.00002)	(0.00002)	(0.00000)	(0.00001)	(0.00001)
# Buildings on lot	−0.00609**	−0.0132**	−0.00700***	−0.0161***	−0.0198***	−0.0184***
	(0.00245)	(0.00566)	(0.00265)	(0.00243)	(0.00310)	(0.00264)
# Floors in building	−0.0277***	−0.0308***	−0.0273***	−0.0267***	−0.0267***	−0.0261***
	(0.000582)	(0.00103)	(0.000662)	(0.000431)	(0.000654)	(0.000534)
Lot frontage	0.00105***	0.00117***	0.00106***	0.000999***	0.00108***	0.00101***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Lot depth	0.000103***	0.000226***	0.000108***	0.000108***	0.000198***	0.000114***
	(0.00002)	(0.00006)	(0.00002)	(0.00002)	(0.00003)	(0.00002)
Building age	−0.00638***	−0.00657***	−0.00633***	−0.00658***	−0.00689***	−0.00654***
	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)
Year altered (1st)	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.000001)	(0.000002)	(0.000001)	(0.000001)	(0.000001)	(0.000001)
Year altered (2nd)	0.00001***	0.00002***	0.00001***	0.00001***	0.00002***	0.00001***
	(0.000002)	(0.000010)	(0.000003)	(0.000002)	(0.000003)	(0.000003)
Office property	1.195***	1.207***	1.193***	1.189***	1.205***	1.186***
	(0.00235)	(0.00796)	(0.00232)	(0.00217)	(0.00529)	(0.00234)
Retail property	1.002***	1.020***	1.006***	0.997***	0.991***	0.992***
	(0.00311)	(0.00841)	(0.00324)	(0.00294)	(0.00457)	(0.00344)
# Residential units	0.000207**	0.000169*	0.000209**	−0.0001***	−0.00017***	−0.000154***
	(0.000100)	(0.000100)	(0.000100)	(0.000020)	(0.000100)	(0.000030)
Liquor lics per BFˆ	0.0125***	−0.00416**	0.0181***	0.00310**	−0.00130	0.00751***
	(0.00386)	(0.00186)	(0.00507)	(0.00133)	(0.000853)	(0.00222)
Stores per BFˆ	0.0311***	0.0575***	0.0344***	0.0107***	0.0144***	0.0112***
	(0.00265)	(0.0193)	(0.00339)	(0.000732)	(0.00234)	(0.000848)
Vacant bldgs per BFˆ	−0.00854***	−0.00557***	−0.00557***	−0.00861***	−0.00827***	−0.00790***
	(0.000798)	(0.00104)	(0.000761)	(0.000311)	(0.000316)	(0.000285)
N	630,550	630,550	630,550	638,085	638,085	638,085

Notes: ˆBF = blockface in results columns 1–3, H-block for columns 4–6; all models include precinct fixed effects and year dummies; all regressions use AV data for 2004–2010. Robust standard errors in parentheses; *$P < 0.10$; **$P < 0.05$; ***$P < 0.01$.

Testing for Heterogeneous Effects

Since the baseline regressions only provide an average effect across all neighborhoods in New York City, we stratify the regressions along dimensions that differentiate neighborhoods in ways that make them more or less prone to criminal and/or commercial activity. For purposes of illustration, we present only the results from H-block models using the sales sample; we will note substantial differences from other models when relevant. We choose to consider the sales sample, because those values should be more responsive to immediate market conditions; since AVs (and the rents off of which they are derived) are "sticky" and not necessarily reflective of existing market conditions, there is less of a reason to expect the values to vary along these dimensions. Considering first the type of commercial activity, we stratify the sample by building classification, i.e., retail or office. We find no statistically significant difference in crime effects across different types of economic activity. This is in contrast to the expectation that crime is less deterred by the safety strategies of disparate retail establishments and more linked to the retail activity itself.[14]

Second, to consider the socioeconomic characteristics of the neighborhoods, we stratify the sample by median household income and by the concentration of nonwhite (specifically, black and Hispanic) residents—all measured at the census tract level using 2000 Census data. We stratify in several ways, testing for thresholds at both ends of the distribution; for ease of exposition we only display a selection of the stratified results. Table 6 displays a summary of these findings, again for H-block aggregates only. Notably, the instruments perform just as well in these stratified regressions as they do for models using the full sample.[15] When we split the sample, the coefficients on the crime variables in the low- to moderate-income neighborhoods (or neighborhoods in the bottom three quarters, where the average household income is $48,706 or lower) are all negative and the coefficient on violent crime is statistically significant.[16] In these neighborhoods, an additional violent crime reduces prices by about 0.7 percent (compared to a null effect for the average neighborhood).[17] We also stratify the sample by race and ethnicity, into high/low nonwhite and then high/low black/Hispanic neighborhoods (based on highest and lowest quartiles). We find that the negative effects from violent crime are significant in neighborhoods with a higher share of black residents (see Table 6); and the higher the share, the larger the effect (an additional violent crime in neighborhoods with higher proportions of black residents results in a 0.5 to 0.7 percent drop in prices). We also see significant negative price effects, from violent and public order crimes, in neighborhoods with low-to-moderate shares of Hispanics (i.e., less than 43 percent Hispanic) and nonwhite residents more generally

[14]We do find statistically significant negative effects for retail properties only (for violent and public order crimes), in the AV-based models; this suggests that with the larger sample we can pick up meaningful differences in building use that indicate retail's more pronounced vulnerability to crime. These results are available from the authors upon request.

[15]The first-stage F-statistics are generally greater than 20, although smaller than the nonstratified regressions that use the full sample; the Sargan Hansen statistics are generally insignificant (with the exception of a few stratifications with $P < 0.05$). Detailed statistics are available from the authors upon request.

[16]Appendix E is a map displaying high- and low-income tracts overlaid with sales, and Appendix F does the same with high- and low-percent African American tracts. We see that sales are clustered in high-income neighborhoods in lower Manhattan, but also along main arterials in Brooklyn, Queens, and the Bronx. These latter sales are in areas that appear to be equally likely to house high, low, or middle proportions of African-Americans and median incomes that are high, moderate, or low.

[17]This significant effect is observed in the blockface models, but goes away in the ring models.

TABLE 6: Stratified 2SLS Models, Sales Prices, H-blocks

	Retail			Office		
Crime Variable	Ln(*PriceSF*)	Ln(*PriceSF*)	Ln(*PriceSF*)	Ln(*PriceSF*)	Ln(*PriceSF*)	Ln(*PriceSF*)
# Violent crimes per H-block	−0.00393			−4.22e-05		
	(0.00374)			(0.00312)		
# Property crimes per H-block		−0.000811			−0.000101	
		(0.000916)			(0.000701)	
# Public order crimes per H-block			−0.00246			−4.30e-05
			(0.00338)			(0.000881)
N	5,516	5,516	5,516	2,202	2,202	2,202
	Bottom 3 quartiles, % Black			Top quartile, % Black		
Crime variable	Ln(*PriceSF*)	Ln(*PriceSF*)	Ln(*PriceSF*)	Ln(*PriceSF*)	Ln(*PriceSF*)	Ln(*PriceSF*)
# Violent crimes per H-Block	−0.00325			-0.00759^{**}		
	(0.00288)			(0.00328)		
# Property crimes per H-block		−0.000475			-0.00260^{*}	
		(0.000618)			(0.00153)	
# Public order crimes per H-block			−0.000980			−0.00433
			(0.000920)			(0.00369)
N	7,645	7,645	7,645	2,370	2,370	2,370
	Bottom 3 quartiles, Med. Income			Top quartile, Median Income		
Crime variable	Ln(*PriceSF*)	Ln(*PriceSF*)	Ln(*PriceSF*)	Ln(*PriceSF*)	Ln(*PriceSF*)	Ln(*PriceSF*)
# Violent crimes per H-block	-0.00744^{***}			−0.0103		
	(0.00252)			(0.00773)		
# Property crimes per H-block		−0.00250			−0.00102	
		(0.00160)			(0.000785)	
# Public order crimes per H-block			−0.00615			0.00239^{**}
			(0.00440)			(0.00105)
N	8,561	8,561	8,561	1,454	1,454	1,454

Notes: ˆBF = blockface in results columns 1–3, H-block for columns 4–6, ring for columns 7–9; all models include precinct fixed effects and year dummies, and a full set of hedonic and H-block controls; all regressions use sales transaction data for 2004–2010. Robust standard errors in parentheses; $^{*}P < 0.10$; $^{**}P < 0.05$; $^{***}P < 0.01$.

(these results are not shown here).[18] Together, the stratified results show that violent crime is most likely to vary across neighborhoods of different demographics, and that the negative effects are concentrated in neighborhoods with lower median incomes and higher shares of black (or nonwhite) residents. Prices in neighborhoods with higher shares of Hispanics, however, are not disproportionately depressed by crime—indeed, crime had no significant effect in those areas.

6. CONCLUSION

The viability of local commercial markets has implications for the overall municipal economy and for submunicipal neighborhood services. Theoretically, crime should affect economic activity by imposing costs on businesses and customers. Although crime is often of great concern to local policymakers, the empirical, quantitative evidence on how it affects local economic activity is sparse. We attempt to fill this gap by testing for the impact of crime on commercial prices and assessed values for a large and diverse jurisdiction. We also test to see if this impact varies by the type of crime, the type of business and the demographic composition of the neighborhoods.

It is not surprising that we initially observe significant and positive associations between crime and sales prices; we contend that this is likely picking up the simultaneity between criminal opportunity and commercial activity. OLS models show a negative relationship between AVs and violent crime, but these coefficients also end up being biased upwards. To improve upon these naïve models, we instrument for crime, and, overall, find that crime does push property values down. The magnitude of the effect, however, varies depending on the type of crime and the geography of crime. Analyses using property transactions, show no significant crime effects at very close range; an additional violent or property crime, however, within a quarter-mile of the property reduces prices by 0.5 and 0.2 percent, respectively. These effects translate into price elasticities ranging from −0.25 to −0.6. In analyses using assessed values, negative crime effects are discernible at very close range (i.e., on the same blockface), such that an additional crime reduces values by 2 to 6 percent, depending on the type of crime. The crime effects stay negative and become smaller at larger multiblock crime geographies: an additional crime results in a 0.4 to 1 percent price drop, or an elasticity of −0.2 to −0.4.

Where we do observe an effect, the magnitude is within the range of what has been calculated in studies of the effects of crime on residential property values. These studies have reported elasticities as small as −0.05 or −0.1 (Lynch and Rasmussen, 2001; Gibbons, 2004; Ihlanfeldt and Mayock, 2010) and as high as −0.5 or −0.6 (Hellman and Naroff, 1979; Gibbons, 2004), suggesting that commercial investors or tenants are similarly responsive to crime in their location decisions as residents are to theirs. This connection makes sense, as much of the economic activity in these commercial properties relies on those same individuals as patrons.

When we stratify the sample by the neighborhood's economic status and prevalence of nonwhite households, we find that the negative effects are strongest in neighborhoods with lower median incomes and higher shares of black (or nonwhite) residents. It appears, then, that these neighborhoods are doubly disadvantaged—lower income and higher minority neighborhoods are already more likely to experience more substantial crime problems, and those crime problems appear to more strongly discourage commercial investment in those areas, as evidenced by the stronger price effects. This is consistent with the

[18] Again, these results are consistent using blockface crime measures, but weaken using ring crime measures.

empirical evidence that documents fewer businesses in lower income and predominantly minority neighborhoods (Immergluck, 1999; Meltzer and Schuetz, 2012; Schuetz et al., 2012). It could also be that businesses and investors use race and income to proxy for neighborhood safety and avoid locations with those demographic signals.

These findings have important implications for neighborhood businesses, commercial property owners and local economic development officials. Our findings suggest that, while modest at the margin, concentrated crime can drive away economic prosperity; if an additional violent crime within a quarter-mile of a property reduces prices by $1.50 per square foot, then properties near 100 violent crimes per year will suffer price drops of $150 per square foot (holding all else constant). Therefore, crime control, especially in poorer communities of color, can revitalize economic activity by reducing the cost of doing business. This means safer streets and more services for those neighborhoods. Our results also point toward policies to manage and disseminate accurate information about a neighborhood's level of safety, an effort that could be assumed by city economic development officials and local stakeholders, such as Community Development Corporations or Business Improvement Districts. Perhaps both crime control and information-based strategies can shift both actual and perceived safety enough to push prices up (or reverse the sustained negative capitalization). Finally, the variation in findings across different geographies and demographic strata also indicates that the effect of crime on property values varies according to the local context—the nature and spatial parameters of the neighborhood are linked to different types and intensities of crime. This suggests that crime control should not employ a uniform strategy, but rather mitigation strategies that are applied differentially across submunicipal neighborhoods.

APPENDIX A.

Crime Categories

Violent Crimes	Property Crimes	Public Order Crimes
Murder & nonnegligent manslaughter	Burglary/breaking & entering	Assault 3 & related offenses
Robbery	Larceny	Burglar's Tools
Forcible rape	Motor vehicle theft	Possession of stolen property
Aggravated assault	Arson	Criminal mischief & related of
		Dangerous weapons
		Fraudulent accosting
		Dangerous drugs
		Prostitution & related offense
		Loitering
		Loitering for drug purposes
		Loitering/deviate sex
		Loitering/gambling (cards, dice)
		Disorderly conduct
		Criminal trespass
		Harassment 2
		Misc. penal law
		NYC health code
		Offenses against public safety
		Offenses against the person
		Other offenses related to theft
		Offenses against pub ord sensibility

APPENDIX B.

Geographies of Crime, Crime Counts

Variable	Obs	Mean	Std. Dev.	Min	Max
Violent crimes per blockface	10,244	2.1	3.2	0	37
Property crimes per blockface	10,244	10.0	24.7	0	518
Public order crimes per blockface	10,244	10.5	15.8	0	356
Violent crimes per H-block	10,244	9.8	12.9	0	148
Property crimes per H-block	10,244	49.6	114.8	0	2,870
Public order crimes per H-block	10,244	51.9	67.7	0	945
Violent crimes per quarter-mile	10,099	124.3	111.2	0	780
Property crimes per quarter-mile	10,099	572.0	819.4	0	7,331
Public order crimes per quarter-mile	10,099	657.3	585.5	0	5,135
Violent crimes per half-mile	10,095	447.7	361.6	0	2,150
Property crimes per half-mile	10,095	2007.9	2606.6	5	16,917
Public order crimes per half-mile	10,095	2404.5	1978.9	11	12,691
Violent crimes per census tract	10,244	48.7	43.4	0	375
Property crimes per census tract	10,244	234.8	273.0	0	2,763
Public order crimes per census tract	10,244	285.0	247.1	0	2,092
Violent crimes per precinct	10,336	1161.7	640.4	0	3,917
Property crimes per precinct	10,336	4706.7	2020.7	0	12,408
Public order crimes per precinct	10,336	6802.3	3481.1	0	21,786

APPENDIX C.

First Stage Results, Sales Prices

Blockface	Property Crime	Violent Crime	Public Order Crime
Chg employ rate (per total units)	−0.008	0.001	0.008
	(0.013)	(0.004)	(0.013)
Precinct crime/unit	91.282**	11.89***	63.414***
	(38.196)	(3.548)	(17.557)
First stage *F*	20.59	29.62	30.92
N	10,155	10,155	10,155
Sargen-Hansen (*P*-value)	0.296 (0.586)	0.369 (.544)	0.479 (0.489)
H-block	Property Crime	Violent Crime	Public Order Crime
Chg employ rate (per total units)	−0.003	0.004	0.079
	(0.090)	(0.016)	(0.068)
Precinct crime/unit	296.61	31.402**	138.242*
	(204.156)	(14.226)	(74.185)
First stage *F*	26.05	43.09	38.74
N	10,155	10,155	10,155
Sargen-Hansen (*P*-value)	0.331 (0.565)	0.351 (.553)	0.811 (.368)

(Continued)

1/4 MI RING	Property Crime	Violent Crime	Public Order Crime
Chg employ rate (per total units)	303.555***	−1.469	−174.408**
	(112.084)	(16.017)	(77.835)
Precinct crime/unit	2443.291**	618.658***	1637.237***
	(990.790)	(92.773)	(452.567)
First stage *F*	137.48	195.78	186.82
N	10,047	10,047	10,047
Sargen-Hansen (*P*-value)	1.033 (.309)	10.996 (.001)	17.877 (0.000)

Notes: All models include full set of hedonic and blockface or H-block controls; all models include precinct fixed effects and year dummies. *$P < 0.10$, **$P < 0.05$, ***$P < 0.01$.

APPENDIX D.

First Stage Results, Assessed Values

Blockface	Property Crime	Violent Crime	Public Order Crime
Chg employ rate (per total units)	−0.007**	−0.006***	−0.008**
	(0.003)	(0.001)	(0.004)
Precinct crime/unit	24.628**	8.177***	29.110***
	(10.784)	(0.430)	(2.231)
First stage *F*	1064.6	1644.06	1858.44
N	630,550	630,550	630,550
Sargen-Hansen (*P*-value)	0.449 (0.503)	1.548 (0.214)	0.428 (0.513)
H-block	Property Crime	Violent Crime	Public Order Crime
Chg employ rate (per total units)	0.017	−0.031***	−0.060***
	(0.017)	(0.004)	(0.020)
Precinct crime/unit	128.22***	37.461***	135.807***
	(31.620)	(1.725)	(10.062)
First stage *F*	1935.01	2852.09	2651.76
N	638,085	638,085	638,085
Sargen-Hansen (*P*-value)	0.021 (.884)	1.307 (.253)	0.401 (.527)

Notes: All models include full set of hedonic and Blockface or H-block controls; all models include precinct fixed effects and year dummies. *$P < 0.10$, **$P < 0.05$, ***$P < 0.01$.

REFERENCES

Bowes, David R. 2007. “A Two-Stage Model of the Simultaneous Relationship between Retail Development and Crime,” *Economic Development Quarterly*, 21(1), 79–90.

Bowes, David R. and Keith R. Ihlanfeldt. 2001. “Identifying the Impacts of Rail Transit Stations on Residential Property Values,” *Journal of Urban Economics*, 50(1), 1–25, doi:10.1006/juec.2001.2214.

Buck, Andrew J., Simon Hakim, and Uriel Spiegel. 1991. “Casinos, Crime, and Real Estate Values: Do They Relate?” *Journal of Research in Crime and Delinquency*, 28(3), 288–303.

Carroll, Deborah A. and Robert J. Eger III. 2006. “Brownfields, Crime, and Tax Increment Financing,” *The American Review of Public Administration*, 36(4), 455–477.

Cantor, David and Kenneth C. Land. 1985. “Unemployment and Crime Rates in the Post-World War II United States: A Theoretical and Empirical Analysis,” *American Sociological Review*, 50(3), 317–332.

Chiricos, Theodor. 1987. "Rates of Crime and Unemployment: An Analysis of Aggregate Research Evidence," *Social Problems*, 34(2), 187–212.

Debrezion, Ghebreegziabiher, Eric Pels, and Piet Rietveld. 2007. "The Impact of Railway Stations on Residential and Commercial Property Value: A Meta-Analysis," *The Journal of Real Estate Finance and Economics*, 35(2), 161–180.

DiLonardo, Robert. 1997. "Financial Analysis of Retail Crime Prevention," in Marcus Felson and Ronald V. Clarke (eds.), *Business and Crime Prevention*. New York: Willow Tree Press.

Ellen, Ingrid G., Johanna Lacoe, and Claudia A. Sharygin. 2013. "Do Foreclosures Cause Crime?" *Journal of Urban Economics*, 74, 59–70.

Fisher, Bonnie. 1991. "A Neighborhood Business Area is Hurting: Crime, Fear of Crime, and Disorders Take Their Toll," *Crime and Delinquency*, 37, 363–373.

Fisher, Jeffrey, Dean Gatzlaff, David Geltner, and Donald Haurin. 2003. "Controlling for the impact of variable liquidity in commercial real estate price indices," *Real Estate Economics*, 31(2), 269–303.

Fuerst, Franz, and Patrick McAllister. 2011. "Green Noise or Green Value? Measuring the Effects of Environmental Certification on Office Values," *Real Estate Economics*, 39(1), 45–69.

Genesove, David. 2003. "The Nominal Rigidity of Apartment Rents," *Review of Economics and Statistics*, 85(4), 844–53.

Gibbons, Steve. 2004. "The Costs of Urban Property Crime," *The Economic Journal*, 114(499), F441–F463.

Gould, Eric D., Bruce A. Weinberg, and David B. Mustard. 2002. "Crime Rates and Local Labor Market Opportunities in the United States: 1979–1997," *The Review of Economics and Statistics*, 84(1), 45–61.

Greenbaum, Robert T. and George E. Tita. 2004. "The Impact of Violence Surges on Neighborhood Business Activity," *Urban Studies*, 41(13), 2495–2514.

Hartley, Daniel. 2010. "The Effect of Foreclosures on Nearby Housing Prices: Supply or Dis-amenity?" Working Paper no. 10–11, Federal Reserve Bank of Cleveland.

Hamermesh, Daniel S. 1999. "Crime and the Timing of Work," *Journal of Urban Economics*, 45, 311–330.

Hellman, Daryl and Joel L. Naroff. 1979. "The Impact of Crime on Urban Residential Property Values," *Urban Studies*, 16(1), 105–112.

Hollinger, Richard C. 1997. "Measuring Crime and Its Impact in the Business Environment," in Marcus Felson and Ronald V. Clarke (eds.), *Business and Crime Prevention*. New York: Willow Tree Press.

Hotelling, Harold. 1929. "Stability in Competition," *Economic Journal*, 39(153), 41–57.

Ihlanfeldt, Keith. 2002. "Spatial Mismatch in the Labor Market and Racial Differences inNeighborhood Crime," *Economics Letters*, 76(1), 73–76.

———. 2006. "Neighborhood Crime and Young Males' Job Opportunity," *Journal of Law and Economics*, 49(1), 249–83.

Ihlanfeldt, Keith and Tom Mayock. 2010. "Panel Data Estimates of the Effects of Different Types of Crime on Housing Prices," *Regional Science and Urban Economics*, 40(2–3), 161–72.

Immergluck, Daniel. 1999. "Neighborhoods, Race, and Capital The Effects of Residential Change on Commercial Investment Patterns," *Urban Affairs Review*, 34(3), 397–411.

Immergluck, Daniel and Geoff Smith. 2006. "The Impact of Single-Family Mortgage Foreclosures on Neighborhood Crime," *Housing Studies*, 21(6), 851–866.

Joh, Kenneth, Mai Thi Nguyen, and Marlon G. Boarnet. 2012. "Can Built and Social Environmental Factors Encourage Walking among Individuals with Negative Walking Attitudes?" *Journal of Planning Education and Research*, 32(2), 219–36.

Kobie, Timothy F. and Sugie Lee. 2011. "The Spatial-Temporal Impact of Residential Foreclosures on Single-Family Residential Property Values," *Urban Affairs Review*, 47(1), 3–30.

Levi, Michael. 2001. "Business, Cities, and Fears about Crimes," *Urban Studies*, 38(5), 849–868.

Levitt, Steven D. 2004. "Understanding Why Crime Fell in the 1990s: Four Factors that Explain the Decline and Six That Do Not." *The Journal of Economic Perspectives*, 18(1), 163–190.

Lin, Ming-Jen. 2008. "Does Unemployment Increase Crime? Evidence from U.S. Data 1974–2000," *The Journal of Human Resources*, 43(2), 413–436.

Linden, Leigh and Jonah E. Rockoff. 2008. "Estimates of the Impact of Crime Risk on Property Values from Megan's Laws," *The American Economic Review*, 98(3), 1103–1127.

Loukaitou-Sideris, Anastasia and Athanasios Sideris. 2009. "What Brings Children to the Park? Analysis and Measurement of the Variables Affecting Children's Use of Parks," *Journal of the American Planning Association*, 76(1), 89–107.

Lynch, Allen. K. and David W. Rasmussen. 2001. "Measuring the Impact of Crime on House Prices," *Applied Economics,* 33(15), 1981–1989.

Meltzer, Rachel and Jenny Schuetz. 2012. "Bodegas or Bagels Shops? Neighborhood Differences in Retail and Household Services," *Economic Development Quarterly*, 26(1), 73–94.

Mills, Edwin S. 1992. "Office rent determinants in the Chicago area," *Real Estate Economics*, 20(2), 273–287.

Mooradian, Robert M. and Shiawee X. Yang. 2000. "Cancellation Strategies in Commercial Real Estate Leasing," *Real Estate Economics*, 28(1), 65–88.

New York City Police Department. 2010. *Citywide Crime Statistics Weekly*, 17(39).

Parker, Karen F. 2008. *Unequal Crime Decline*. New York: New York University Press.

Paternoster, Raymond and Shawn D. Bushway. 2001. “Theoretical and Empirical Work on the Relationship between Unemployment and Crime,” *Journal of Quantitative Criminology*, 17(4), 391–407.

Quigg, Laura. 1993. “Empirical Testing of Real Option-Pricing Models.” *The Journal of Finance*, 48(2), 621–640.

Raphael, Steven and Rudolf Winter-Ebmer. 2001. “Identifying the Effect of Unemployment on Crime,” *Journal of Law and Economics*, 44(1), 259–283.

Rizzo, Mario J. 1979. “The Effect of Crime on Residential Rents and Property Values,” *The American Economist*, 23(1), 16–21.

Rosenthal, Stuart S. and Amanda Ross. 2010. “Violent Crime, Entrepreneurship, and Cities,” *Journal of Urban Economics*, 67(1), 135–149.

Sampson, Robert J. 2012. *Great American City: Chicago and the Enduring Neighborhood Effect*. Reprint edition. Chicago: University Of Chicago Press.

Schuetz, Jenny, Jed Kolko, and Rachel Meltzer. 2012. “Are Poor Neighborhoods ‘Retail Deserts’?” *Regional Science and Urban Economics*, 42(1), 269–285.

Schwartz, Amy E., Scott Susin, and Ioan Voicu. 2003. “Has falling crime driven New York City’s real estate boom?” *Journal of Housing Research*, 14(1), 101–136.

Taylor, Ralph B. 1995. “The Impact of Crime on Communities,” *The Annals of the American Academy of Political and Social Science*, 539,(1), 28–45.

———. 1997. “Social Order and Disorder of Street Blocks and Neighborhoods: Ecology, Microecology, and the Systemic Model of Social Disorganization,” *Journal of Research in Crime and Delinquency*, 34(1), 113–55.

Thaler, Richard. 1978. “A Note on the Value of Crime Control: Evidence from the Property Market,” *Journal of Urban Economics*, 5(1), 137–145.

U.S. Census Bureau. “County Business Patterns: How the Data Are Collected and Methodology.” Available online at https://www.census.gov/econ/cbp/methodology.htm. Last accessed January 29, 2016.

Weisburd, David, Elizabeth R. Groff, and Sue-Ming Yang. 2013. “Understanding and Controlling Hot Spots of Crime: The Importance of Formal and Informal Social Controls,” *Prevention Science* 15(1), 31–43.

Whitaker, Stephan and Thomas J. Fitzpatrick IV. 2012. “The Impact of Vacant, Tax-Delinquent, and Foreclosed Property on Sales Prices of Neighboring Homes,” Working Paper no. 11–23R, Federal Reserve Bank of Cleveland.