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Crime and Residential Choice: A Neighborhood Level Analysis of the Impact of Crime on Housing Prices

George E. Tita · Tricia L. Petras · Robert T. Greenbaum

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Abstract Crime serves as an important catalyst for change in the socio-economic composition of communities. While such change occurs over a long period of time, crime is capitalized into local housing markets quickly and thus provides an early indicator of neighborhood transition. Using hedonic regression, we quantify this ''intangible cost'' of crime and extend the crime-housing price literature in several important ways. First, we disaggregate crime to the census tract level. Second, using longitudinal data, we examine changes in crime in addition to the neighborhood levels of crime. Third, we differentiate between the effects of property crime and violent crime. Fourth, we also disaggregate our sample into groups based on per capita income of the census tract. Finally, we show that it is vital to account for the measurement error that is endemic in reported crime statistics. We address this with an instrumental variable approach. Our results indicate that the average impacts of crime rates on house prices are misleading. We find that crime is capitalized at different rates for poor, middle class and wealthy neighborhoods and that violent crime imparts the greatest cost.

Keywords Housing markets · Neighborhood transition · Hedonic modeling · Costs of crime

G. E. Tita (✉)
UC Irvine Criminology, Law and Society, 2307 SE II, Irvine, CA 92697-7080, USA
e-mail: gtita@uci.edu

T. L. Petras · R. T. Greenbaum
John Glenn School of Public Affairs, The Ohio State University, 1810 College Rd, Columbus, OH 43210-1336, USA
e-mail: petras.6@osu.edu

R. T. Greenbaum
e-mail: greenbaum.3@osu.edu

Introduction

The characteristics of place play an undeniably important role in determining the levels and patterns of crime within communities. Poverty, racial composition, residential instability, and levels of home ownership are just some of the ecological factors correlated with local levels of crime. Moreover, classic ecological theories of crime argue that it is the transitory period when urban neighborhoods move towards concentrated disadvantage that they exhibit the highest levels of crime and delinquency (Park and Burgess 1925; Shaw and McKay 1942). From the perspective of the systemic model of crime, the resulting concentration of poverty along with continued population instability inhibits the development of informal social control (Bursik and Grasmick 1993). As empirical studies have demonstrated, crime serves as an important catalyst for change in the socio-economic composition of communities (Alba et al. 1994; Cullen and Levitt 1999; Liska and Bellair 1995; Krivo and Peterson 1996; Morenoff and Sampson 1997).

The cumulative effects of crime on the socio-economic reconstitution, or concentration of certain groups, within neighborhoods plays out over decades. However, changing levels of crime are likely to induce more immediate responses at the individual level. Increases in crime will directly impact an individual's perception of safety in a neighborhood. In turn, as perceptions regarding the safety of one's own neighborhood deteriorate, urban residents often choose to move from impacted communities in search of less threatening environs (Cullen and Levitt 1999; Dugan 1999; Morenoff et al. 2001). Coupled with macroeconomic changes that have lead to dramatic changes in the types and spatial distribution of employment opportunities, such as "deindustrialization" (Bluestone and Harrison 1982; Wilson 1996), crime and the fear of crime leads to flight from the city into the suburbs which leaves in its wake areas of concentrated poverty and racial/ethnic enclaves in the urban core (Jargowsky 1997; Massey and Denton 1993). As housing markets serve as the arenas in which the impact of crime first manifests itself, these markets can potentially serve as early indicators of neighborhood decline. Therefore, a more complete examination of how crime impacts local housing prices will ultimately lead to a better understanding of the larger issue pertaining to how crime impacts residential stability. Such an examination is lacking in the criminological literature.

While acting as a catalyst of neighborhood change, the impact of crime on local housing markets also has important costs at the individual and family levels. These costs are imposed both on victims and non-victims by directly altering choices and by the secondary effects of those changes. In addition to the psychological and monetary costs borne by those who move, crime imposes additional costs on those who either cannot or choose not to leave an area. First, from a systemic model of crime perspective, indirect costs are incurred when fleeing residents fracture the social bonds and ties necessary for the development of local informal social control needed to deter and abate local crime (Bursik and Grasmick 1993; Sampson 2004). In essence, crime induces flight, which leads to more crime.

Residents are negatively impacted financially when crime suppresses local housing prices, thereby stunting an important mechanism for the accumulation of wealth. For well over a century, US policy has encouraged home ownership (Megbolugbe and Linneman 1993), and numerous papers have examined the relationships between home ownership and household and societal outcomes (e.g., Dietz and

Haurin 2003). While home ownership is often viewed as a way to help enable households to build wealth, threats to the value of that investment may limit its appeal. One such threat is crime, which may reduce the desirability of ownership in affected neighborhoods. Thus, an examination of housing prices serves as an ideal measure of the impact of changes in crime on neighborhood desirability.

This research builds upon the existing housing literature within the fields of urban studies and economics by elevating the prominence of crime as a determining factor in local pricing. The housing literature often includes the crime rate in hedonic regression models predicting property values. Unfortunately, crime is often included in these analyses without much thought afforded to the ways different types of crime influence individual behavior. We estimate the impacts of total crime, property crime and violent crime separately. Similarly, the geographic level at which the housing market is defined is often disjointed with the levels at which crime is believed to influence individual choices. Housing markets are often localized and likely respond to local rather than citywide changes in crime; employing a citywide crime index results in a distorted picture of how crime impacts housing values for any particular neighborhood. We define housing markets at the census tract level. While our unit of observation is individual home sales, we include tract level community characteristics (e.g., income, population density, demographic composition, and crime) as predictors of a home's sale price. Finally, in the extant housing literature, crime is assumed to homogeneously impact housing prices across a city. We posit instead that the impact of crime on housing prices differs across neighborhoods based upon socio-economic composition as measured by income.

The remainder of the paper is organized as follows. The next section examines the relationship between crime and housing prices. We then present our hedonic econometric models and data. We model the relationship between crime and housing values using more than 43,000 housing transactions between 1995 and 1998 in Columbus, Ohio. We argue that the systematic underreporting of crime leads to biased coefficients and that an instrumental variable approach is needed to help address this measurement error. We conclude with the regression results and a discussion of our findings. The empirical results indicate that the average impacts of crime rates on house prices typically reported in the literature are misleading. The disaggregation of place by income, the disaggregation of total crime into their component crimes, and inclusion of changes in crime rates all prove to be important elements in understanding the true relationship between crime and price. Although property crimes tend to dominate total crime indexes, violent crime and changes in violent crime have the largest negative impact on housing values across all neighborhoods.

Crime, Mobility, and Housing Markets

This research builds on earlier work that examines the impact of crime on the residential choices of victims and non-victims. If crime induces residential changes, the costs to society include not only the actual costs of moving but also the additional costs of potentially sub-optimal reallocations of homeowners. Previous research indicates that crime does induce moves. For example, Dugan (1999) found that victimization near one's home increases the probability that individuals move to a new residence.

However, crime also imparts costs to non-victims, both directly in terms of altered location decisions and more indirectly through changes in neighborhood characteristics and safety. Neighborhoods change when rising crime rates induce urban flight out of high crime neighborhoods (Cullen and Levitt 1999). The impact of urban flight can vary profoundly by neighborhood type. Cullen and Levitt show that higher-income households are much more likely to move than lower-income households, which leads to greater concentrations of poverty. Likewise, Morenoff and Sampson (1997) found that crime rates in Chicago were related to subsequent changes in residential choices that differed based on racial composition. While high initial levels of crime lead to losses in both black and white populations, increases in homicide lead to whites moving out and black populations growing in those neighborhoods. Liska and Bellair (1995), too, found that over four decades, violent crime rates led to changes in the racial composition in a sample of U.S. cities. Not only does crime alter the makeup of neighborhoods through ''white flight,'' but issues of safety may be even more likely to affect the decisions of where movers decide to locate in the first place than to induce moves (Frey 1979; Garland and Stokols 2002; Morrow-Jones 2000; Taylor 1995). For example, while Katzman (1980) found little evidence to support that the perception of crime influences relocation decisions of local residents, he did find strong evidence that perceptions of crime play an important role in determining where people are willing to move. Families with children and higher incomes individuals were more sensitive to crime when choosing place of residence.

If crime induces neighborhood changes that lead to increased concentrations of poverty, this can start a difficult cycle leading to even more crime (Miethe and Meier 1994). When the end result of crime and white flight is the creation of a series of neighborhoods in which minority members are spatially concentrated, then additional dynamics impact housing values as well. When a neighborhood becomes racially homogenous, the pool of potential homebuyers shrinks to only the members of that group. Given that members of minority groups tend to have less wealth than whites, a situation develops in which too few buyers with too few dollars serves to suppress local prices (Flippen 2004). Falling house prices help perpetuate this the cycle of increased poverty and crime, as mobility is often impaired when house prices fall (Chan 2001).

Individuals' decisions to make a move and then to subsequently sell a house can often take months or years, and the neighborhood changes described in the previous paragraph take even longer. The impacts of changes in crime rates on the local housing prices should occur with much shorter time lags, however, as the crime disamenity can be very quickly capitalized into the housing market.

Indeed, there are numerous examples in the housing literature showing the impact of crime on housing. Feinberg and Nickerson (2002) found a significant relationship between lagged crime rates and mortgage defaults. Buck and colleagues found relationships between levels of crime and housing values in and around Atlantic City, NJ (Buck et al. 1991a, b; Buck and Hakim 1989), and Thaler (1978) found that property crime reduces house values by approximately three percent. Likewise, Dubin and Goodman (1982) and Haurin and Brasington (1996) found that higher crime rates reduced housing prices in hedonic regression models estimating the impact of public school quality on house prices. Rizzo (1979) examined the impact of crime on both housing values and rents among the 71 ''community areas'' of Chicago and found that crime reduces both local rents and property values.

Burnell (1988) found that crime in neighboring communities also has a similar negative effect on housing values as crime in the same community. By reducing property values in Boston, increases in crime also reduced tax revenues thus creating fiscal problems for the local municipal government (Hellman and Naroff 1979; Naroff et al. 1980).

In an analysis of 92 U.S. SMSAs, Manning (1986) found no significant impact of the percentage change in the crime rate on home price appreciation. Likewise, Lynch and Rasmussen (2001) found that crime had a very small impact on average house sales values. However, they showed that the impact was much larger in high crime areas. Gibbons (2004) found that crimes such as vandalism, graffiti, and arson had a greater deleterious impact on house prices in London than burglaries and interpreted that to mean that perceptions of neighborhood safety may be very important because crimes such as vandalism and graffiti are very visible signals of disorder (see Skogan 1990; Wilson and Kelling 1982). Schwartz et al. (2003) found that falling crime rates contributed to the real estate boom in New York City using precinct level crime data and sales of apartment buildings, not individual housing units. Unlike the other studies examining house prices, both Manning (1986) and Schwartz et al. (2003) measured changes in the crime rate rather than levels. We follow in the tradition of these recent papers in terms disaggregating crime types and geography and by also examining the impact of changes in crime.

Contributions of the Current Research

Much of this existing literature on the crime-housing market nexus is cross-sectional and utilizes crime data aggregated to a high geographic level, only examines the impact of overall crime levels, and/or estimates an average impact across all types of neighborhoods. Such analysis ignores important neighborhood level and temporal variation. We overcome these limitations in several important ways.

First, rather than using highly aggregated data at the city, county, or metropolitan level as do most studies of crime and housing,[1] our data is more finely disaggregated to the census tract level. Phenomena such as crime are very neighborhood specific, and analysis at larger geographic scales may mask important sub-area variation and result in city or metropolitan level average estimates that are misleading at best. The advantage of using a much smaller geographic unit of analysis is that the homogeneity within each unit is increased while simultaneously the variation across units is also increased. This enables a fuller exploration of the impacts of location sensitive factors thought to influence housing prices within a metropolitan area such as local housing policy, local economic conditions, school quality, or crime.

Second, using hedonic modeling of housing transactions over time, we examine the impact of *changes* in crime in addition to *levels* of crime. Many neighborhoods have historically maintained above or below average levels of violence. In a cross section, it is not surprising to find that house prices for constant-quality houses are lower in higher crime areas. Homeowners concerned about safety are likely familiar with historic levels of violence and incorporate information on crime rates when they choose where to buy (Taylor 1995). Although families are likely to sort based on levels, we hypothesize that it is important to also examine changes in crime rates because the changes in rates are more likely to induce changes in behavior

[1] Three notable exceptions are Rizzo (1979), Naroff et al. (1980), and Dubin and Goodman (1982).

(i.e., moves). We measure changes in behavior by examining whether changes in crime levels affect housing values when holding the crime rate constant.

Third, we also disaggregate the crime by the type of crime. Different crimes are likely to impose different costs to victims (Cohen 1990, 2005; Skogan and Maxfield 1981). As noted above, Gibbons (2004) finds that crimes of disorder have a larger impact on local housing prices than do serious property crimes. Though support has been mixed (Dugan 1999), the expectation is such that violent crimes will induce residential moves on the part of local victimization far more often than property crimes. Therefore, we follow suit and estimate the impact of not just overall crime on housing values, but we also distinguish between the impacts of violent and property crime.

Finally, we examine whether the impact of crime varies across different types of neighborhoods. It has been shown that local business owners capitalize the cost of changes in violence differently based upon pre-existing neighborhood conditions (Greenbaum and Tita 2004). There is ample evidence to suggest that crime will differentially impact house prices depending on neighborhood characteristics as well. Cullen and Levitt (1999, p. 24) find that increases in crime induce flight among white, married, well-educated households while ''...household heads who are young, male, black, have children, are single, or have lower educational attainment are more likely to stay in central cities.'' Similarly, Morenoff and Sampson (1997) find that neighborhoods that experienced increases in levels of violence experienced a net loss of white population and a net gain in black population. Therefore, we categorize neighborhoods based on per-capita income at the tract level.

We offer several competing hypotheses regarding how and why crime will differentially impact housing prices depending upon levels of per capita income in the neighborhood. First, we expect that changes in violent crime rates will have a larger impact in higher-income neighborhoods in which violent crime is typically a less frequent event. These events often receive much greater media attention, which in turn is likely to inflate local levels of fear (e.g., Best 1999). It can be argued that residents, along with the potential pool of homebuyers, in lower income neighborhoods are more adept at discerning between the general and specific risks of violent crime (Dawes 1988; St. John 1987). That is, those populations with greater exposure to living with violence may better appreciate the non-random nature of events than people residing where violence is rare but can seemingly ''happen to anyone.'' For low-income neighborhoods, it is likely that levels of violence will already be capitalized into housing prices and that a change in levels will have little impact on price. An alternative hypothesis is that wealthier residents have a greater menu of options at their disposal to addresses increases in crime, which may mitigate its affect in those neighborhoods. We also expect that more property crime in some neighborhoods may signal greater wealth and thus offer more attractive returns to criminals.

Additionally, crime is known to be under-reported in certain types of neighborhoods, particularly those comprised of poor or largely immigrant residents. Such underreporting has been documented in surveys that capture whether or not victims reported the crime to the police. Based upon the National Crime Victimization Survey, lower income, younger, and male victims are more likely to under-report crimes while homeowners are more likely to report crimes (Skogan 1999). If this induces a positive relationship between the amount of reported crime and housing prices, the results of estimating the overall impact of crime indexes on housing values will be biased. As we describe in the next section, we take a two-pronged approach to address this potential bias. We not only examine the impact of different types of crimes in different types of neighborhoods, but we also take an instrumental variable approach to estimating the impact of crime on housing values.

Methods

Our first step is to examine whether variations in constant-quality housing prices can be partially explained by levels and changes in crime rates. Hedonic modeling can be used to infer prices of specific property attributes that are not traded individually in the market. When buying a house, the purchaser buys not only the structure and the land but also the neighborhood and other characteristics associated with that house. Because the whole package must be bought, the buyer does not know the value of each individual component or attribute that makes up the property. Hedonic modeling allows the inference of the prices of attributes by using standard regression techniques with selling price of the property as the dependent variable and the various attributes of the property as independent variables. The estimated coefficients for the variables can then be interpreted as the price per unit of the attribute with which it is associated.

Thus, we estimate hedonic regressions that measure house prices as a function of the characteristics of the house (square feet, number of bedrooms, number of bathrooms, etc.), its location (characteristics of the population, etc.) and both levels and changes in crime rates in the census tract in which the house is located. Controlling for the house and location characteristics, we test whether changes in local and neighboring crime rates significantly affect housing prices:

$$H_{int} = \beta_0 + \beta_1 S_i + \beta_2 L_n + \beta_3 \Delta L_n + \beta_4 C_{nt-1} + \beta_5 \Delta C_{nt} + \delta_t Y_t + \gamma_t Z_t + \eta_i D_i + \varepsilon_{it} \quad (1)$$

where H_{int} is the natural log of the transaction price of home i in neighborhood (census tract) n at time t, S_i is a vector of time-invariant structural housing characteristics, L_n is a vector of locational attributes measured in 1990, ΔL_n is a vector of change in locational attributes measured from 1980 to 1990, $C_{nt\text{-}1}$ is the crime rate (level of crime) in the census of tract house i in the year previous to the sale, ΔC_{nt} is the change in that crime rate from $t - 1$ to t,[2] Y_t is a vector of time indicator variables that equal 1 when the ith house is sold in year t and 0 otherwise, Z_t is a vector of seasonal time indicator variables, D_i is a vector of structural indicator variables, and ε_{it} is the random error. β_1 and β_2 are vectors of coefficients on the structural characteristics and locational characteristics, β_3 is a vector of coefficients that capture the impact of a change in locational characteristics in a house's census tract between 1980 and 1990 on that house's transaction price, β_4 is a coefficient that captures the impact of neighborhood crime levels on a house's transaction price, β_5 is a coefficient that captures the impact of a change in crime in a house's census tract on that house's transaction price, and δ_t and γ_t represent the vectors of time coefficients that account for different market and seasonal factors. The vector η_i represents the coefficient for various structural dummies.

[2] We also estimated (not reported) models that measure the change between years $t - 2$ and $t - 1$. Measuring change in this way has the advantage that all of the measured change will have occurred by the time the house sale has completed. However, there are two major drawbacks to this more distant lag. One is that it doesn't incorporate changes that are more contemporaneous, and perhaps more relevant, with the sale. The second drawback is that this requires one additional year of data, and such an estimation results in the loss of approximately one-third of the observations in our study.

The notion that crime is undercounted and that there is a ''dark figure'' of unrecorded crime is widely recognized (MacDonald 2001). The rate of underreporting is related to both the nature of the offense and to socio-economic characteristics of the person reporting the crime (Skogan 1999). In a study on the relationship between the under-reporting of property crime and unemployment, MacDonald (2000) finds that race, gender, employment status, and level of education are among the factors that contribute to an individual's likelihood to report a crime. If crime rate undercounting is systematically correlated with covariates used in ordinary least squares analysis, coefficient estimates estimating the impact of crime on housing values will be biased.

Two approaches address the potential biases due to crime underreporting. First, we estimate Eq. (1) separately for ''low,'' ''medium,'' and ''high'' income neighborhoods. Low- and high-income neighborhoods are defined as the bottom and top quarter of the distribution of income in census tracts in 1990. Medium income neighborhoods are the middle 50% of the distribution. Since it is expected that underreporting of crime varies across neighborhoods, this analysis provides test of whether results are indeed sensitive to the underreporting problem.

This categorical analysis is also substantively important because of the notion that crime is likely capitalized into different types of neighborhood differently. Residents of neighborhoods in which crime is a more common occurrence are likely to react to changes in crime differently than in neighborhoods in which crime is more rare. For example, business decisions were shown to be most sensitive to surges in homicide rates in the lowest crime neighborhoods (Greenbaum and Tita 2004). Here, average per capita income serves as a proxy for sorting the types of neighborhoods. The average per capita income is correlated to many neighborhood characteristics such as racial composition, unemployment, and crime level.[3]

Secondly, the underreporting issue is addressed through the use of a two-stage least squares instrumental variables (IV) approach. Use of an IV helps address the potential bias of the crime coefficient due to its correlation with the error term. Potential instruments must be correlated with the crime rate, but uncorrelated with the error term. In the analysis of violent crime, murder is an ideal instrument. Murder is significantly correlated to violent crime and has been shown to be a good proxy for violent crime (Fox and Zawitz 2000). Further, ''no other crime is measured as accurately and precisely'' (Fox and Zawitz 2000, p. 1), therefore it is much less likely to be correlated with the error term.

Data

We use housing, crime, and demographic data at the census tract level for the city of Columbus, Ohio, a Midwestern city with a population in 2000 of approximately 711,000. Data from three distinct sources are combined to create a panel of 43,577 housing transactions in 189 census tracts across the years 1995–1998. The precise address level home sale and crime data are aggregated to census tracts, and the home sale and crime incident dates are annualized.

[3] Indeed, alternatively categorizing types of neighborhoods based upon an index of concentrated disadvantage (based upon percentages of unemployment, poverty, female headed households, and black residents) did not change the findings.

Our crime data, provided by the Columbus Police Department (CPD), consist of all Part I crimes including homicide, rape, robbery, aggravated assault, burglary, larceny, and auto theft. The data include all incidents known to the police where an official report was coded and entered into the CPD's data management system. These data were geocoded using the incident location as the spatial reference point and then aggregated into counts at the census tract level. We created annual rates per one thousand for the period 1994–1998 for total crimes, violent crimes, and property crimes. Although rates per 100,000 persons are typically reported for citywide data, a rate of crime per 1000 persons is more appropriate for use at the census tract level, which, in our sample, has a mean of 3848 people per tract. As can be seen in Table 1, the average total crime rate for the full sample is 274.9 crimes per thousand residents.

Housing data for the years 1995 through 1998 for Columbus are taken from the First American Real Estate Solutions[4] database. In addition to valuation based on sales price at the date of last sale and assessment value at the date of the last assessment, the data contain many characteristics of each property. Characteristics include factors such as dwelling size, number of bedrooms, number of bathrooms, age of the structure, whether the property is owner-occupied, and the presence of amenities such as swimming pools, air conditioning, fireplaces, decks, and so on. The average price of homes that sold between 1995 and 1998 was $154,704.

Household demographic and economic characteristics come from the 1980 and 1990 Decennial Census Summary Tape Files (STF3). Census variables measure neighborhood racial composition, demographic composition, and economic factors such as average tract income, poverty rates, and unemployment rates.

The sample used includes 43,577 individual house sales and includes all single-family houses sold in Columbus. Houses with a reported size of zero square feet, a number of rooms equal to zero, and a lot size of zero square feet were excluded from the analysis. Observations for which at least one of these values is non-zero are kept for analysis, and an indicator variable signaling a zero value for square feet, number of rooms, or lot size is included. Properties that had missing information on the year the house was built were assigned the average age of other homes in the same census tract, which was also denoted with the ''year built estimated'' indicator variable. To investigate whether the impact of crime on housing prices varies across types of neighborhoods, the sample was subdivided into categories based on the per capita income of the census tract in which the house is located. Separate regressions were then run for each category. The low-income category includes observations in tracts in the bottom quartile based on per capita income in 1990, the middle-income category includes observations in the middle 50% of tracts, and the high-income category includes observations in the top quartile of per capita income.

The variable means, both for the overall sample and by income category, are reported in Table 1. Notable highlights include the finding that crime decreased in the average low-income tract during the mid 1990s but increased in medium and high-income areas. This relationship holds for total, property and violent crime. Housing and socio-economic conditions also differ between low-income neighborhoods and medium and high-income neighborhoods. Areas beyond the lowest 25th percentile of income have approximately a 50% greater fraction of owner occupied dwellings (as opposed to rental units), and they also experience vacancy rates that are half of those experienced in more disadvantaged neighborhoods. In 1990, the disadvantaged

[4] Formerly known as Amerestate, Inc.

Table 1 Variable means for full sample and by income category

Variable	All	Low income	Medium income	High income
Dependent variable				
House price 1995–1998	154,704	88,170	152,607	193,311
ln(House price)	11.294	10.628	11.314	11.635
Number of transactions	43,577	8,954	18,203	16,420
Crime characteristics 1994–1998				
Total crime rate in previous year (per 1,000)	274.900	259.723	304.990	224.278
Change in total crime rate	– 3.831	– 70.184	3.557	62.723
Violent crime rate in previous year	14.703	18.101	15.346	8.929
Change in violent crime rate	1.826	– 1.463	3.708	1.611
Property crime rate in previous year	260.197	241.623	289.643	215.350
Change in property crime rate	– 5.657	– 68.721	– 0.152	61.111
Murder rate in previous year	0.200	0.371	0.081	0.258
Change in murder rate	– 0.026	– 0.090	– 0.003	0.000
Structural characteristics 1995–1998				
Size of house in 1000 square feet	2.001	2.075	2.012	1.949
Number of rooms	5.309	5.829	4.968	5.403
Number of bathrooms	1.620	1.294	1.423	2.016
Lot size in 1000 square feet	4.558	4.603	5.007	4.036
Age of house	35.106	64.793	33.545	20.647
Age of house squared	2003.605	4720.245	1689.638	870.252
Neighborhood characteristics				
% White population in 1990	0.754	0.518	0.807	0.912
Average rent in 1990	345.212	254.760	339.289	466.571
Total population in 1000s in 1990	3.848	3.494	3.396	5.315
Per capita income in 1000s in 1990	13.564	7.074	12.997	22.598
Population density in 1000s in 1990	1.998	3.084	1.755	1.266
% Owner occupied housing units in 1990	0.530	0.357	0.559	0.672
% Vacant housing units in 1990	0.071	0.116	0.055	0.053
% Unemployment in 1990	0.074	0.153	0.055	0.026
% Young people in 1990	0.277	0.330	0.272	0.226
Change in % Black population, 1980–1990	1.062	0.222	1.468	1.122
Change in % Hispanic population, 1980–1990	0.527	0.245	0.582	0.737
Indicator variables				
Spring	0.254	0.246	0.254	0.259
Fall	0.258	0.261	0.262	0.253
Winter	0.197	0.226	0.199	0.180
Year: 1996	0.248	0.228	0.251	0.256
Year: 1997	0.258	0.264	0.263	0.250
Year: 1998	0.284	0.320	0.274	0.275
Year built estimated	0.160	0.263	0.156	0.109
Zero lot size	0.343	0.123	0.278	0.535
Zero rooms	0.140	0.157	0.166	0.102
Zero size of house	0.096	0.074	0.123	0.076

neighborhoods also had the highest levels of population density, unemployment, and proportion of the population under the age of 25. The highest income neighborhoods were 91% white in 1990, while the low-income neighborhoods were 52% white.

Results

Upon estimating Eq. (1) for total, violent, and property crime, the Pagan–Hall (1983) statistic indicates that the presence of heteroskedasticity in the error terms and rejects the null hypotheses of homoskedastic errors ($P < 0.050$). As Moulton (1986, 1990) points out, this is often the case when regressions are fit to micro level data (e.g., home sales) that are drawn from clusters (e.g., census tracts). If left unaddressed, the uncorrected standard errors obtained through OLS tend to be biased, which could lead to misleading interpretations of hypothesis tests (Moulton 1986, 1990). Several strategies can be employed to improve the estimates of the standard errors on the regression coefficients and provide more reliable *t* statistics, including the use of robust standard errors and clustering of observations (e.g., Pepper 2002; Wooldridge 2003). Theory often suggests grouping of data based upon geographic clusters of cities, states or regions because of important differences across those units. For instance, local tax rates, school districts, policing, and other public services are all place specific attributes that play similar roles in determining the housing prices within a particular jurisdiction. When analyzing housing prices at the county, state, or regional level, clustering on jurisdictional units would clearly be important. In the current case, however, clustering by same geographic areas (tract) is not theoretically supported given that all of the areas are drawn from the same city and therefore are subject to the same laws and economic policies. Furthermore, by estimating our models separately for three different groups of neighborhoods based on income levels, we have imposed additional structure and have eliminated one of the likely sources of unequal variance. Therefore, to correct our standard errors, we weight them in all specifications using the robust estimates in STATA (2003), which are based upon Huber (1967) and White (1980, 1982) and addresses the more general case of heteroskedasticity from an unknown source.[5]

The first two rows of Table 2 report the results for estimation of Eq. (1) for the total crime index, for the violent crime index, and for property crimes. Coefficients on the structural and neighborhood characteristics as well as the indicator variables have been omitted from the table for sake of brevity. Although the coefficient on the total crime rate lagged for the previous year (“Level”) is estimated to be positive, it is not significant even at the ten percent level. The coefficient on the change in crime variable is more in line with expectations. It is statistically significant and negatively affects housing prices. The second column of Table 2 presents estimates of the impact of violent crime, while the third column presents results of the estimation of the impact of property crime on housing values. The estimated impacts of property crimes are similar to those of the total crime index because the two are so highly correlated, and this same pattern was found across all of the various specifications. As with total and property crime, the coefficient on the temporally lagged level of violence variable is small and not statistically significant, although the coefficient on a change in violence is significant at the one percent level and the sign is in the expected (negative) direction.

Earlier, we hypothesized that the impact of crime on housing values is likely to differ based upon the characteristics of the communities in which crimes occur. To examine this, we repeat the above analysis by looking at the difference across low-, medium-, and high-income neighborhoods. The remaining six rows of Table 2 present the coefficients on the lagged crime level and change in crime rate coeffi-

[5] We also estimated all models using both tract fixed effects and by robust cluster procedures that adjust for possible correlation among observations within census tracts. The basic findings were robust across the three methods, although there was slight difference in the sizes of the standard errors on the coefficients. These results are available from the authors.

Table 2 Summary of crime coefficients for hedonic regressions of ln(sale price) for full sample and by income category with robust standard errors

Income category	Specification	Total crime		Violent crime		Property crime	
		Coeff.	*P*-value	Coeff.	*P*-value	Coeff.	*P*-value
All	Level	0.00001	0.110	0.00003	0.759	0.00001	0.135
	Change	– 0.00003	0.009	– 0.00030	0.000	– 0.00002	0.019
Low	Level	0.00053	0.000	0.00636	0.000	0.00056	0.000
	Change	0.00048	0.000	0.00460	0.121	0.00050	0.000
Medium	Level	– 0.00001	0.101	– 0.00006	0.676	– 0.00001	0.064
	Change	– 0.00001	0.068	– 0.00019	0.009	– 0.00001	0.052
High	Level	– 0.00003	0.000	– 0.00035	0.026	– 0.00003	0.000
	Change	0.00006	0.001	– 0.00079	0.000	0.00007	0.000

cients for these regressions. It is evident from the results that the impacts of crime levels and changes vary across the different neighborhoods, and this is confirmed with a Chow test (Chow 1960) that rejects the restricted model in favor of separate neighborhood regressions. The coefficient on the lagged total crime rate was found to be positive and significant for the low-income category, but the magnitude of the coefficient is larger than in the full sample. For the medium-and high-income categories, the lagged total crime coefficients are significant and negative, as expected. For the medium-income category, the coefficient on the change in total crime rate is negative as expected. The coefficient on change in total crime rate is negative and significant at the 10% level, but it is positive and significant in both the low-and high-income categories.

We also get unexpected results using the violent crime rate or property crime rate as the measure of local crime. While the estimates for the property crime regressions are again very similar to the total crime estimates, the coefficients for the lagged violent crime levels are significant only in the low- and high-income categories and have a positive sign in the low-income category. The changes in violent crime rate coefficients are more in line with expectations, significant and negative, except in the low-income category, where the coefficient is positive.

These peculiar findings that, in some cases, both higher levels and increases in crime led to increased housing values warrant further investigation. Such findings, however, are not unique to our data (e.g., Case and Mayer 1996; Gibbons 2004; Lynch and Rasmussen 2001). As mentioned above, aggregate measures of crime often suffer from under-reporting, and the under-reporting is likely to vary systematically based upon the severity of crime and the community context in which the crime occurs. This measurement error is likely to lead to biased estimates of the coefficients on the crime variables, which can plausibly help explain some of the unexpected results. Further evidence of this is that the most surprising findings (positive signs on all of the crime level and change coefficients) are in the low-income neighborhoods, which the literature points to as the most susceptible to underreporting.

Short of collecting better data, the standard econometric solution to the measurement error problem is to use instrumental variables. As explained above, the homicide rate is used as the instrument for the various crime indexes because it is correlated with those indexes but is unlikely to be correlated with the error term due to its more reliable reporting. In cases such as this in which the model is exactly identified, the IV two-stage least squares model is identical to the efficient GMM estimator (Hayashi 2000). The results of Durban–Hausman–Wu tests indicate that use of the instruments is justified (P-value < 0.00001) (Durbin 1954; Hausman 1978; Wu 1973).

Table 3 reports the coefficient estimates of Eq. (1) using IVs for the levels and changes in the various crime rates. Not surprisingly, the coefficients of the housing structural characteristics are significant and have signs in the expected direction for

Table 3 Hedonic regression of ln(sale price) for full sample using instrumental variables approach and robust standard errors

Variable	Total crime IV		Violent crime IV		Property crime IV	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Crime characteristics 1994–1998						
Total crime rate in previous year	– 0.00009	0.000				
Change in total crime rate	– 0.00020	0.159				
Violent crime rate in previous year			– 0.00163	0.000		
Change in violent crime rate			– 0.00060	0.005		
Property crime rate in previous year					– 0.00009	0.000
Change in property crime rate					– 0.00015	0.113
Structural Characteristics 1995–1998						
Size of house in 1000 square feet	0.00425	0.000	0.00420	0.000	0.00424	0.000
Number of rooms	0.07335	0.000	0.07333	0.000	0.07323	0.000
Number of bathrooms	0.06717	0.000	0.07131	0.000	0.06870	0.000
Lot size in 1000 square feet	0.02361	0.000	0.02364	0.000	0.02360	0.000
Age of house	– 0.01516	0.000	– 0.01349	0.000	– 0.01468	0.000
Age of house squared	0.00011	0.000	0.00010	0.000	0.00011	0.000
Neighborhood characteristics						
% White population in 1990	0.48682	0.000	0.45999	0.000	0.48316	0.000
Average rent in 1990	– 0.00100	0.000	– 0.00074	0.000	– 0.00092	0.000
Total population in 1000s in 1990	– 0.00425	0.000	– 0.00439	0.000	– 0.00436	0.000
Per capita income in 1000s in 1990	0.05039	0.000	0.04655	0.000	0.04936	0.000
Population density in 1000s in 1990	– 0.02183	0.000	– 0.02561	0.000	– 0.02357	0.000
% Owner occupied housing units in 1990	0.28319	0.000	0.22739	0.000	0.26804	0.000
% Vacant housing units in 1990	– 1.20347	0.000	– 1.24155	0.000	– 1.22247	0.000
% Unemployment in 1990	– 0.34638	0.146	– 0.39643	0.091	– 0.35461	0.135
% Young people in 1990	0.98035	0.000	0.94797	0.000	0.98106	0.000
Change in % Black population, 1980–1990	– 0.00134	0.362	– 0.00021	0.833	– 0.00090	0.459
Change in % Hispanic population, 1980–1990	0.00832	0.003	0.00712	0.007	0.00800	0.003
Indicator variables						
Spring	– 0.02455	0.003	– 0.02317	0.004	– 0.02411	0.003
Fall	0.01061	0.194	0.00955	0.236	0.01028	0.205
Winter	– 0.01823	0.050	– 0.02022	0.025	– 0.01885	0.040
Year: 1996	0.03731	0.000	0.03602	0.000	0.03771	0.000
Year: 1997	0.11783	0.000	0.10860	0.000	0.11525	0.000
Year: 1998	0.18382	0.000	0.18343	0.000	0.18453	0.000
Year built (estimated)	– 0.07269	0.000	– 0.07622	0.000	– 0.07436	0.000
Zero lot size	0.13346	0.000	0.12747	0.000	0.13137	0.000
Zero rooms	1.96934	0.000	1.97690	0.000	1.97160	0.000
Zero size of house	– 1.11863	0.000	– 1.12257	0.000	– 1.12068	0.000
Constant	9.70690	0.000	9.70369	0.000	9.69797	0.000
N	43577		43577		43577	
Adjusted R^2	0.4284		0.4408		0.4331	

all regressions. Likewise, the coefficients on all neighborhood characteristics, with the exceptions of the unemployment rate in 1990 and the change in percent black population from 1980 to 1990, were found to be significant across the three specifications. These findings are consistent with other hedonic pricing studies.

Table 4 again omits all but the crime coefficients and replicates the results across all neighborhoods and adds the results for low-, medium-, and high-income neighborhoods. For all income categories combined, the coefficients on the temporally lagged levels of crime are all now negative and significant for total (– 0.00009), violent (– 0.0016), and property crime (– 0.0001). Only the coefficient on change in violent crime (– 0.0006) is statistically significant.

Once again, the results of the IV estimation are more in line with expectations when the sample is disaggregated by income category for analysis. High levels and higher rates of change in levels of violence both have a negative impact on local housing prices in low- and high-income neighborhoods. Neither levels nor changes in violence appear to influence housing prices in middle-income areas. For total crime and property crime, the coefficients for both the level and change in crime are negative across the different neighborhoods, with the exception of the coefficients for change in the crime indices for middle-income areas. The only coefficients that are statistically significant at the five percent level for total and property crime are the negative coefficients for the level of crime in high-income areas and the unexpectedly positive coefficients for changes in total and property crime in the middle-income neighborhoods.

Discussion

Our results show that estimation of the average impact of the total crime index on housing values across the city of Columbus is negligible. Our analysis also shows that this finding is misleading. Failure to account for the dark figure, or the underreporting of crime rates, leads to biased regression coefficients. Failure to distinguish among crime types overlooks the fact that property crime dominates the total crime index and misses the fact that violent and property crime rates have distinct impacts on the attractiveness of particular neighborhoods. Failure to distinguish among different neighborhood types within the city would suppress the finding that the impact of crime varies across neighborhood types and thus leads to different housing

Table 4 Summary of crime coefficients for hedonic regressions of ln(sale price) for full sample and by income category using instrumental variables approach and robust standard errors

Income category	Specification	Total crime IV		Violent crime IV		Property crime IV	
		Coeff.	*P*-value	Coeff.	*P*-value	Coeff.	*P*-value
All	Level	– 0.00009	0.000	– 0.00163	0.000	– 0.00009	0.000
	Change	– 0.00020	0.159	– 0.00060	0.005	– 0.00015	0.113
Low	Level	– 0.00971	0.264	– 0.01114	0.095	– 0.02769	0.623
	Change	– 0.01051	0.260	– 0.03632	0.013	– 0.02951	0.622
Medium	Level	– 0.00072	0.444	0.04121	0.180	– 0.00087	0.380
	Change	0.00173	0.001	0.01606	0.499	0.00152	0.003
High	Level	– 0.00007	0.000	– 0.00122	0.000	– 0.00007	0.000
	Change	– 0.00015	0.288	– 0.00045	0.035	– 0.00011	0.230

market outcomes. Finally, failure to distinguish between underlying crime levels and changes in crime rates ignores that each has a distinct impact on the decisions people make.

In our initial analysis, no attempts were made to correct for the measurement errors inherent in official crime statistics. In a number of the instances in which results were statistically significant, the sign on the coefficient was opposite of the expected direction. That is, higher levels of total crime were found to actually increase housing prices. There is precedence for this anomalous finding, however, within the literature. For instance, Lynch and Rasmussen (2001) find a positive effect of the number property crimes on housing values when using reported crime data. To address this unexpected result, they use a weighting scheme based on the costs associated with the severity of different offenses to develop a crime index. However, this weighted crime index still relies on reported crime data and does nothing to address the potential bias the reliance on official data may induce in model estimation. Gibbons (2004) also reports an initial finding that property crime increases housing values. However, by adopting an instrumental variable approach, he is able to show that burglary rates are, in fact, unrelated to housing prices. Case and Mayer (1996), too, find crime to have a positive effect on property values when using citywide total crime rates in a comparison of home prices in the Boston area but do not explain this counterintuitive result.

We conjecture that these common counterintuitive findings are at least partially a function of the underreporting of crime that plagues official crime statistics. When crime is systematically underreported, bias becomes a major issue and OLS estimation is inappropriate. One crime, however, has consistently been demonstrated to be much less to immune to problems of underreporting—homicide. Further, research has shown homicide is a good proxy for other types of non-lethal violence as the spatial distribution of lethal and non-lethal violence is very similar (Tita and Cohen 2004). In order to address the potential under reporting of other violent crime, we instrument total, violent, and property crime with the homicide rate. When compared to the OLS results, these estimates make intuitive sense, thus arguing in favor of the use of instruments. The results are most pronounced in the low-income neighborhoods, where the underreporting is likely to be most severe. Failure to instrument would lead to the incorrect conclusion that more total, violent, and property crime all increase property values in these neighborhoods. The two-stages least squares results using the homicide IV indicate that higher levels of crime depress housing values.

By considering the differential impact of crime by type of crime, we are able to demonstrate that the rather negligible impact of the total crime rate on housing values is misleading. Once we look beyond the total crime index, we find that violent crime does negatively impact home values. The total crime rate is dominated by property crimes, which are likely to be inconsistently underreported. Use of an instrument helped overcome this.

Furthermore, we demonstrate that total, property, and violent crime differentially impact housing prices across different types of neighborhoods. For instance, results from the specifications using homicides as an instrument for violent crime indicate that violent crime and changes in violent crime negatively impact housing values across all neighborhoods and across the sub samples of low and high-income neighborhoods. Somewhat unexpectedly, this impact is largest in the low-income neighborhoods. Perhaps residents in higher income neighborhoods have a greater menu of potential responses to increases in violent crime, including garnering support for more public safety measures and increasing personal safety expenditures such as alarm systems and fences.

Having crime and housing data over time, we are also able to capture the impact both of levels of crime as well as changes in crime. Controlling for structural housing and neighborhood characteristics, housing prices in a low-income neighborhood with one additional violent crime per thousand (level) are on average 1.1 percent lower. The average housing price in low-income neighborhoods is $88,170, so this represents a loss in value of $970. Controlling for the same factors, a house in a low-income neighborhood with an increase (change) of one more crime per thousand has on average 3.6% lower housing prices. This represents a loss in value of $3,174. The total loss due to one addition crime per 1,000 is $4,144 in these neighborhoods. These results are certainly substantively significant. In contrast, housing prices in a high-income neighborhood with an additional violent crime per thousand (level) has on average 0.1 percent lower housing prices and an increase (change) of one more violent crime per thousand has on average 0.05 percent lower housing prices. The average housing price is $193,311 in high-income neighborhoods, so these translate into losses of $193 and $97, respectively, for a total loss of $290. Clearly there are issues of equity, as the negative impact of violent crime is greatest in low-income neighborhoods where residents can least afford the loss in wealth.

The disproportionate impact of violent crime on housing values in disadvantaged neighborhoods has especially distressing implications. First, research has demonstrated that the race and ethnicity of the local residential population plays an important role in determining housing prices. Flippen (2004) finds that controlling for socio-economic variables, housing values appreciate much more slowly in neighborhoods with predominately black or Latino residents when compared to comparable white neighborhoods. By further suppressing valuation, crime retards the accumulation of wealth for precisely those members of society that, arguably, benefit the most from rising home prices. Low-income homeowners often fail to take advantage of other investment opportunities such as securities markets. Therefore, homeownership may offer the best available instrument to facilitate the bridging of the wealth-gap between members of the majority and minority groups. It is important to realize that the wealth-gap far exceeds the income-gap (Oliver and Shapiro 1995). Furthermore, it is the gap in the accumulation of wealth and not the gap in wages that is most responsible for the intergenerational nature of poverty (Flippen 2004).

The time frame of our current research is not long enough to explore how changes in housing prices mediate the impact of crime on the socio-economic transitions of neighborhoods. However, the fact that the impact of crime varies both by crime type and by neighborhood characteristics suggests need for caution in interpreting the results of those studies that purportedly do explore the crime-neighborhood transition nexus (e.g., Alba et al. 1994; Cullen and Levitt 1999; Krivo and Peterson 1996; Liska and Bellair 1995; Morenoff and Sampson 1997). None of these studies analyze the impact of crime on specific types of neighborhoods within a city per se, but rather simply control for neighborhood characteristics.

The good news is that, for the period examined in our study, the crime rates fell in the low-income neighborhoods. For example, the violent crime rate in these neighborhoods fell from 20.213 violent crimes per thousand in 1994 to 15.554 in 1997. Our model predicts that this fall of 4.66 violent crimes per thousand in low-income tracts, holding all else equal, resulted in an increase of $15,737 from the 1995 mean housing value of $71,853.[6] The mean price of housing in low-income neighborhoods roe to $111,947 in 1998, for a total increase of $40,094. Thus, the increase attributable to the reduction in violent crime in these census tracts was approximately 39%, which is in line with what Schwartz et al. (2003) found in New York City where they attribute approximately one-third of an increase in housing prices to the decline in violent crime.

The current study is not without its limitations. First, the time frame used in this research covers a relatively short time period. This period can be classified as a time of general prosperity, income growth, and housing appreciation throughout much of the U.S. Similarly, crime over this period continued to fall. As noted earlier, however, crime only decreased in disadvantaged neighborhoods, which clearly suggests that these changes drive citywide crime rates. We are currently exploring data availability in a number of cities that will cover a longer time period thus allowing us to explore how more macro-economic conditions influence the crime-housing price relationship. A longer time series will also allow us to explore the direct linkages between crime, housing prices and socio-economic transition of neighborhoods. Second, we fail to control for spatial dynamics of crime (or high crime neighborhoods) in that they may exhibit a distance decay function. Close proximity to a high crime neighborhood may be more detrimental to home values than local levels of crime, especially when local crime levels are at or below the levels observed in neighboring areas. Finally, by modeling housing prices as a function of community level features as well as house specific measures, we are arguing that factors operate at multiple levels. Though our basic hedonic model is both sound and indicative of the accepted methodology within the housing literature, the adoption of hierarchical linear models (HLM) would represent an innovative break-through worth exploring.

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[6] $[(-4.66^* - 0.011)^* \$71,853] + [(-4.66^* - 0.036)^* \$71,853]$

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