Low-Income Housing Development and Crime

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ABSTRACT

This paper examines the effect of rental housing development subsidized by the government's Low-Income Housing Tax Credit program on local crime. We take advantage of changes in the formula used to determine the eligibility of census tracts for Qualified Census Tract (QCT) status, which affects the size of the tax credits developers receive for building low-income housing. QCT status attracts real estate development from other parts of the county, differentially improving the housing stock in the poorest census tracts. Low-income housing development, and the associated revitalization of neighborhoods, brings with it significant reductions in violent crime that are measurable at the county level. There are no detectable effects on property crime, perhaps because of changes in reporting behavior among residents.

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1. Introduction

Both the efficiency and equity of place-based housing programs for low-income households are frequently called into question. To the extent that such housing programs promote development primarily in low-income neighborhoods, they may only serve to increase the concentration of poverty, which can have deleterious effects on communities, particularly in terms of limiting access to good jobs, schools, and other means to achieve upward economic and social mobility. However, when well-planned and targeted, subsidized housing programs may help to revitalize struggling communities and generate positive externalities that help to turn declining neighborhoods around.

An important potential externality associated with affordable housing development involves its implications for neighborhood criminal activity. There are two primary ways in which low-income housing development could affect crime. First, new low-income housing may alter the composition of an area's population by displacing current residents and attracting new ones. The extent to which immigrants or emigrants are prone to criminality could have immediate effects on the level and nature of crimes in an area. Second, housing construction or rehabilitation may lead the existing population to become less criminal. If new low-income housing development eliminates vacant lots that foster criminal behavior, attracts a greater police presence, motivates residents to be more vigilant, or more generally helps to rejuvenate a community, it could affect the extent of local criminal activity.

This paper examines the effect of rental housing development subsidized by the government's Low-Income Housing Tax Credit (LIHTC) program on neighborhood crime. We take advantage of changes in the formula used to determine the eligibility of census tracts for Qualified Census Tract (QCT) status, which affects the size of the tax credits developers receive for building low-income housing. We find evidence that the structure of the LIHTC steers new low-income development toward poorer areas. Using QCT coverage measures as instruments for neighborhood revitalization, we find that while new and rehabilitated housing infrastructure in disadvantaged areas has little measured effect on property crime, it is associated with reductions in robberies and aggravated assaults. The effects are observed at the county level, suggesting that crime is not merely being shifted from one neighborhood to another.

The finding that improvements in the housing stock in the poorest neighborhoods is associated with reductions in crime runs counter to well-known results from research on the Moving to Opportunity (MTO) experiment. Studies on the impacts of MTO, which randomly assigned low-income households in blighted communities to better neighborhoods, have found that improvements in one's physical environment do not lead to reductions in criminal behavior (Harcourt and Ludwig 2006). These results were interpreted as refuting the so-called "broken windows" hypothesis, which holds that more serious crime can be prevented by targeting minor disorder such as graffiti, loitering, and litter. However, since households who move experience changes not only in their physical surroundings, but also in many other aspects of their lives, including, for example, their social networks, the usefulness of MTO to study the impact of neighborhood change has been called into question (Sampson 2008). We find that holding social networks constant, improvements in the physical environment in which people live does appear reduce violent crime, lending some support to the broken windows hypothesis.

The paper is organized as follows. In the next section, we provide an overview of previous research into the effects of low-income housing development as well as the link between neighborhood conditions and crime. In Section 3, we discuss the structure of the LIHTC program. We describe the data in Section 4 and discuss the way in which we exploit the LIHTC program's structure to identify the effects of subsidized housing development in low-income neighborhoods on different types of crime in Section 5. In Section 6, we present our results. Section 7 concludes.

2. Background

2.1. Low-income housing

A frequent charge leveled against public housing programs is that they have concentrated poverty, particularly in inner-city neighborhoods (Massey and Denton 1993, Carter et al. 1998, Cunningham and Popkin 2005). Encouraging subsidized housing development in areas already rife with poverty has not only provided incentives for low-income residents to stay, but has also attracted economically disadvantaged residents from elsewhere to these neighborhoods. The even higher poverty and segregation that results can have severe negative consequences in terms of access to employment and education opportunities. A large literature suggests that the characteristics of one's place of residence have important implications for child and adult outcomes (see Ellen and Turner 1997 for a review), and the negative consequences of childhood exposure to violence and drug dealing in areas of concentrated urban poverty may be particularly severe (Katz and Turner 2008).

However, any tendency for such housing developments to concentrate low-income households must be weighed against their potential implications for overall community revitalization. Low-income housing developments may not only eliminate vacant or abandoned lots and provide decent housing to disadvantaged populations, but they might also help to attract new business and jobs as well as increase neighborhood policing and surveillance. To the extent that low-income housing developments can remedy some of the immediate social and economic ills of an area and generate positive spillovers, they may serve as a springboard to reducing poverty in the future.

Recent research on the effects of what is now the federal government's flagship project-based housing program, the LIHTC program, has highlighted these potential offsetting effects. The LIHTC program, which is described in more detail in the next section, provides tax incentives to developers to encourage low-income housing development, with particularly large breaks afforded to those building in high-poverty areas. Ellen et al. (2009) find that there is little evidence that the LIHTC program is increasing the concentration of poverty, and that, in fact, it might be doing the opposite. They argue that, especially when coupled with explicit community revitalization efforts, developments funded under the LIHTC program can help to rejuvenate struggling communities. However, they contend that in general, special breaks for developers that site in particularly low-income areas are misguided, as they steer projects disproportionately toward high poverty neighborhoods and limit the extent to which developments find their way to lower poverty communities that might provide opportunities to low-income households to move closer to better jobs and schools. The policy tradeoff is one of revitalizing the most blighted areas or reducing the cost to low-income residents of moving into higher income areas.

Baum-Snow and Marion (2009) also find that the LIHTC program promotes significantly more housing development in low-income areas, but consistent with work by Eriksen and Rosenthal (2008), also highlight the heterogeneous effects of the program across neighborhoods.

Taking advantage of the formula structure of the program in the 1990s and using a regression discontinuity approach, Baum-Snow and Marion find that new low-income housing units increased property values in declining areas (where home prices had previously been trending downward), while at the same time reduced incomes in gentrifying areas (where home prices had been trending upward).

Also, in line with Eriksen and Rosenthal's work as well as past research on other types of place-based subsidized housing (Murray 1999, Sinai and Waldfogel 2005), Baum-Snow and Marion show that LIHTC units crowd out new unsubsidized rental construction, mainly in gentrifying areas. Burge (forthcoming) and Lang (2010), meanwhile, find little evidence that the LIHTC program actually serves to lower rental rates substantially. It is therefore more accurate to think of the LIHTC as improving the stock of housing available to low-income residents, as opposed to increasing the stock of available affordable housing. This improvement in the quality of housing provides a unique opportunity to study the link between neighborhood conditions and crime, and more specifically, to revisit the broken windows hypothesis.

2.2. Crime and broken windows

The broken windows hypothesis, which is largely based on a series of experiments conducted by Stanford psychologist Phillip Zimbardo, received a large amount of attention when it was articulated by James Q. Wilson and George Kelling in an *Atlantic Monthly* magazine article in 1982. The idea behind broken windows is that minor markers of social disorganization in a neighborhood, such as a prevalence of loitering, graffiti, panhandling, and prostitution, would signal that "no one cared" about a community, and that more serious antisocial behavior was tolerated. The hypothesis was embraced in many major cities, particularly New York City and Los Angeles, where significant resources have since been allocated to more aggressive enforcement of misdemeanor laws with the goal of maintaining a semblance of order and thus potentially preempting more serious offenses (Harcourt and Kling 2006). In more recent years, a number of smaller cities have followed in these footsteps. In 2008, for example, Toronto adopted a broken windows policing approach, its police chief Bill Blair noting that "there is a value in taking care of the little things…where there is a sense of disorder and lack of safety, people stop going out into their parks, they don't send their kids out, they lock their doors" (Robertson 2008, page 4).[1]

While the idea has support in policy circles, the empirical evidence on broken windows is mixed. Though Eck and Maguire (2000) suggest that there is little evidence to suggest that policing methods inspired by the broken windows hypothesis played a role in the decline in crime rates during the 1990s, Corman and Mocan (2005) find that more misdemeanor arrests provide a signal of stepped up police vigilance and do serve as a deterrent to more serious crimes. A number of studies in sociology, psychology, and criminology have also found some support for the broken windows hypothesis, albeit often in small samples or only exploiting cross-sectional variation (Sampson and Cohen 1988, Giacopassi and Forde 2000, Kelling and Sousa 2001). Also, while not focused on the broken windows hypothesis, Cook and Macdonald (2010) find evidence that commercial areas in Los Angeles designated as Business Improvement Districts experienced reductions in crime. Additionally, results from studies using controlled experiments suggest that signs of petty criminal behavior can instigate more of such behavior, leading to the spread of disorder within communities (Keizer et al. 2008).

However, recent reevaluations of existing data and several influential articles exploiting the MTO experiment have cast doubt on the relevance of the broken windows hypothesis. Reexamining the data used in the Kelling and Sousa (2001) study, Harcourt and Ludwig (2006) show that broken windows policing may have had less of an effect than previously believed. Moreover, Harcourt and Kling present new evidence from the MTO experiment, which randomly assigned housing vouchers to approximately 4,600 low-income households in blighted communities in five major U.S. cities. These vouchers allowed lottery winners to move to less disadvantaged neighborhoods, providing a unique opportunity to circumvent traditional problems associated with studying how neighborhood conditions affect crime and other outcomes. In particular, while there may be a strong correlation between housing conditions and crime, whether this relationship is causal is unclear; where people live is at least partly a matter of choice, and those who reside in high-poverty vs. low-poverty areas may differ along many dimensions, only some of which can be measured and controlled for in non-experimental

[1] Other major cities, however, have taken the opposite approach, stressing leniency for minor crimes and devoting more resources to preventing and prosecuting serious offenses. For example, in Philadelphia, a newly appointed district attorney is reversing policies tough on drug offenders, noting that "we need to focus on the people who are shooting people" (Eckholm 2010).

analyses. MTO's random assignment led individuals who were otherwise identical to live in different communities, which in turn allowed for causal inferences.

Exploiting the MTO design, Harcourt and Ludwig find that randomly assigning people to move to less disorderly communities does not result in reductions in individual criminal behavior. Harcourt and Ludwig as well as Kling and Ludwig (2007) and Kling et al. (2005) focus on the effects of specific measures of neighborhood social disorder and find that they are not strong predictors of violent behavior among MTO participants. In fact, though most are insignificant, the estimated coefficients on some measures of neighborhood characteristics have the opposite sign of what the broken windows hypothesis would imply; young males in particular appear to engage in more property crime after moving to more orderly neighborhoods. The authors take this as evidence that broken windows policies are not sound strategies for reducing overall crime.

While the MTO experiment provided a wealth of information about the effects of neighborhoods on child and adult outcomes, it arguably did not provide the ideal setting to study the broken windows hypothesis (Sampson 2008).[2] Individuals who move from one neighborhood to another are not only introduced to new physical surroundings, but also may experience dramatic changes in the size and depth of their social networks, which Sampson et al. (1997) argue are major predictors of violent crime. Children often switch schools, and both familial and community resources available to parents may change.[3] As a result, differences in criminality among those who moved and those who did not move may not be entirely attributable to changes in the physical environment, but rather could be due to a multitude of factors that individuals and their families experience when they relocate residentially. The random assignment in MTO is compelling, but because MTO randomly assigned individuals to neighborhoods with less disorder, as opposed to reducing disorder in randomly selected neighborhoods in which the residents lived, the MTO results arguably represent lower bounds on the effect of neighborhood disorder on the criminality of residents.

Several sociological and ethnographic studies have drawn links between subsidized housing and increases in criminal activity (Roncek et al. 1981, Farley 1982, McNulty and Holloway

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[2] A collection of articles published in the first issue of the 114th volume of the *American Journal of Sociology* (published in 2008) was devoted to the debate over what can and cannot be learned from the MTO experiment about neighborhood effects.

[3] Indeed, one interpretation of the MTO experience is that disadvantaged children become the "new kids" in neighborhoods that may be only marginally better than the ones they left behind (Quigley and Raphael 2008).

2000). As these studies point out, the demographic groups more often involved in crime, including low-income blacks and Latinos, are disproportionately found in low-income housing. Building new affordable housing could affect crime by attracting individuals from other neighborhoods who might be more prone to criminal activity. Building new affordable housing in a neighborhood might also affect measured crime rates by influencing the propensity of existing residents to engage in or report certain types of crime. Finally, there is some evidence to suggest that the physical design of low-income housing itself, and in particular high-density public housing, may foster criminal activity (Newman 1973). Illicit behavior is rarely confined to housing projects themselves, though; criminal activity often radiates into surrounding neighborhoods, creating a drag on schools, police resources, as well as commercial and residential investment.[4]

Past studies on the relationship between crime and the presence of subsidized housing generally focus only on select cities and time periods. Further, they have largely considered only the effect of public housing projects, some of which have been demolished under HOPE VI and others of which are in the process of rehabilitation.[5] Indeed, case studies of new HOPE VI developments find sharp accompanying reductions in crime (Katz and Turner 2008), which may generalize to other types of neighborhood revitalization. No studies have examined the relationship between crime and low-income housing subsidized by the LIHTC, which is now the federal government's largest program to finance the development of affordable rental housing for low-income households.

3. The LIHTC program

Originally created by Congress as a part of the Tax Reform Act of 1986, the LIHTC program provides tax credits to developers to encourage the construction of affordable rental housing. Now one of the largest federal programs aimed at addressing the housing needs of lower-income

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[4] Husock (2003) describes the effects of public housing on communities, interviewing one property manager in East Harlem, New York who observes, "We're surrounded on all sides by [public housing] – they're an eyesore, and there's an awful lot of runoff, whether crime or drugs… If we had even half the number of projects, we'd be the next East Village, with our proximity to midtown and the Number 6 subway train going right through the neighborhood" (page 36).

[5] HUD's HOPE VI program, which began in 1992, provides block grants to cities to transform the most severely distressed public housing projects into mixed-income developments.

populations, the LIHTC program subsidized over 31 thousand projects representing some 1.8 million units between 1987 and 2007. LIHTC-funded units represent a large and growing share of total renter occupied housing units, rising from less than 1% in the early 1990s to about 5% currently.[6]

Potential developers must apply for tax credits under the LIHTC program. States award tax credits drawing on funds allocated annually by the federal government. These funds are limited, with annual per capita allocations starting at $1.25 at the program's inception to the current $1.95 (Ellen et al. 2009).[7] State housing agencies have discretion over which projects receive tax credits, but federal law requires states' allocation plans give priority to projects that serve the lowest income households and that ensure affordability for the longest period of time.

Developers can qualify to receive credits to build low-income housing in any area as long as the project meets one of two criteria. First, a project can qualify if at least 20% of households that will occupy the development have incomes below 50% of the area median gross income (AMGI). Second, a project can qualify if at least 40% of households that occupy the units have incomes below 60% of the AMGI. A project that satisfies one of these requirements and caps annual rents for its low-income units at 30% of the income limit defined for the area for at least 30 years can receive a 10-year stream of tax credits under the program.[8] Because the size of the credit depends in part on the share of units set aside for low-income households, in practice, over 90% of the units in LIHTC projects qualify as low-income.

New legislation passed by Congress as part of the Omnibus Reconciliation Act of 1989 stipulated that LIHTC projects built in very low-income areas, termed Qualified Census Tracts (QCTs), or in areas with relatively high construction costs, termed Difficult Development Areas (DDAs), are eligible for a 30% increase in their credit allocation.[9] Prior to 2002, a census tract qualified as a QCT if 50% of its households had incomes below 60% of the AMGI unless the total population of designated QCTs within a metropolitan area exceeds 20% of that

[6] There were 35.045 million renter occupied housing units in 2007 according to the American Housing Survey. http://www.census.gov/hhes/www/housing/ahs/ahs07/ahs07.html.

[7] The allocation to each state was $1.25 per resident each year between 1986 and 2001, with the exception of 1989, when it allocated $0.93 per resident. Funding rose to $1.75 per resident in 2001. Since 2003, funding has been indexed to inflation.

[8] The LIHTC originally required developers receiving credits to maintain rent controls for 15 years. The window has since been increased to 30 years.

[9] A DDA is a nonmetropolitan or metropolitan area with high construction, land, and utility costs relative to its AMGI. Projects located in both a QCT and DDA are eligible for only one subsidy increase.

metropolitan area's population. In cases in which the population requirement is not met, tracts within a metropolitan area are ranked according to the share of households with incomes below 60% of the AMGI. Working down that list, tracts are designated eligible until adding another tract would breach the 20% threshold.[10]

As part of the Community Renewal Tax Relief Act of 2000, Congress added another criterion to determine eligibility. Effective January 1, 2002, a census tract can qualify for QCT status if at least 50% of its households have incomes below 60% of the AMGI or if the poverty rate of the tract is at least 25% (still subject to the same population restriction). This change immediately increased the number of designated tracts from 7,700 in 2001 to over 9,900 in 2002 (Hollar and Usowski 2007). The share of the U.S. population living in QCTs jumped from under 10% to over 13%.[11]

QCT designations have changed further over time with the release of new decennial census data and with changes in metropolitan area definitions. HUD determined QCT status for tracts prior to 2003 using data from the 1990 Decennial Census. For 2003 onward, HUD determined QCT status using data from the 2000 Decennial Census. The release of updated data resulted in substantial changes in QCT designations, largely because of changes in poverty and income levels within tracts, but also partly because of changes in geographic boundaries of tracts and their corresponding metropolitan areas.

Following the release of updated census data in 2003, the share of the population in QCTs fell only about one percentage point to 12%, but there was high turnover within and across areas in tracts designated as QCTs. Just considering those tracts existing throughout the time period,

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[10] The subsidies involved can be very large. For example, a $10 million project with land and financing costs of $2 million has a so-called "eligible basis" of $8 million. The tax credit calculation begins with this amount and is adjusted for the number of rent-restricted units in the development. Over four-fifths of developments are 100% rent-restricted, but if the project in question dedicated only 75% of units to low-income residents, then the so-called "qualified basis" would be 0.75 × $8 million, or $6 million. If the project is not located in a QCT or DDA, then the qualified basis is multiplied by the tax credit rate to determine the annual subsidy. Most new construction and rehabilitation projects are currently eligible for a 9% tax credit rate, in which case the developer would receive $540,000 per year for the first ten years after the project is completed. In this example, tax credits account for 54% of the original $10 million cost. If the project were in a QCT or DDA, the qualified basis is increased by a factor of 1.3, which in this case would result in a qualified basis of $7.8 million and an annual subsidy of $702,000. Over 70% of the original cost would be covered by subsidies in this case. Developers generally sell the futures of tax credits to investors in order to raise the capital required to fund construction; McClure (2006) finds that after syndication, the LIHTC has funded about 55% of construction costs for projects built after 2000.

[11] These population figures are based on the 1990 Decennial Census. Prior to 2003, the geographic boundaries HUD used were based on 1990 Census definitions.

1,702 tracts gained QCT status in 2003, while 1,847 lost it. Some 2.3 million households, or about 2% of all households, that were not previously in QCTs prior to 2003 were in QCTs after 2003, while nearly the same number of households that were in QCTs prior to 2003 were not afterward.

In intercensal years, QCT designations can change to reflect metropolitan area redefinitions, which affect the AMGI with which to compare local household incomes to determine whether a tract meets the criteria that at least 50% of its households have incomes below 60% of the AMGI. There were no changes between 2003 and 2006, but in 2007, 662 tracts changed QCT status after the release of new metropolitan area definitions.

Figures 1-3 show the geographic distribution of QCTs in 2000, 2002, 2003, and 2007 for the three counties that encompass Dallas, Texas, Washington, DC, and Cleveland, Ohio. In Dallas County, 75 of the 415 tracts were designated qualified as of 2000 (based on 1990 tract definitions and Decennial Census data). Those 75 tracts were home to 13.6% of the 1990 population and covered 11.4% of the county's land area. The introduction of the poverty criterion for QCT designation in 2002 added 14 tracts to the list of those qualified in the county and resulted in sizable increases in the population and land area covered by QCTs in the county (to 16.9% and 14.1%, respectively). With the release of 2000 census data as well as several changes in tract boundaries in 2003, there was an expansion in QCT designations in the southwestern part of the county as well as a removal the designation for several gentrified central city tracts. More minor changes in QCT designations accompanied the changes in MSA boundaries and AMGI announced in 2007. Washington, DC is an example of a generally poorer county, with relatively large shares of the population and land area in QCTs. DC also experienced some dramatic changes in designations between 2000 and 2007, in part driven by the loss of QCT status in rapidly gentrifying areas just north of the capital. Meanwhile, Cuyahoga County, whose county seat is Cleveland, had a more stable distribution of QCTs. With roughly one-fifth of the population but only one-tenth of the land area designated qualified between 2000 and 2007, Cuyahoga highlights how in many areas, QCTs tend to be the more densely populated tracts.

4. Data

4.1. Department of Housing and Urban Development

Data on QCT status and low-income housing developments are from the U.S. Department of Housing and Urban Development (HUD). HUD publishes annual updates to QCT designations that we compiled to create a panel of tracts with their respective QCT status between 2000 and 2007. For each tract, we also have data from the Census Bureau on poverty and income that determine QCT status each year. Data from the 1990 Decennial Census were used by HUD to determine QCT designations prior to prior to 2002, while data from the 2000 Decennial Census were used to determine designations in 2003 and after.

HUD also provides data on low-income housing tax credit projects. These data include all projects receiving any tax credits through the LIHTC program and, for most developments, have information on the exact location of the project, total number of units, number of low-income units, type of project (new construction, rehabilitation, existing, or some combination), amount and type of funding, whether the project is targeted at a particular group (families, the elderly, disabled, homeless, etc.), and other information. The data have information on the year the project was placed in service (roughly when construction was completed and the property was ready for occupancy) and the year that funds were allocated to the project; for about one third of the projects, the two years are the same, while for nearly all of the remaining two thirds, the year placed in service is either one or two years after the year the funds were allocated to the project.

For each year between 1987 and 2007, we determine the number of projects and units placed in service by type of project and by whether they are located in QCTs. Of the 31,087 projects in the U.S. (excluding Puerto Rico, Guam, and the U.S. Virgin Islands), there are 254 projects that have no year placed in service information,[12] and an additional 330 projects are missing information on number of units. Of the 30,503 projects remaining, 2,394 projects have no tract geography information. However, we have street addresses for a large share of these projects,

[12] These observations also have no information on the year funds were allocated.

and we were able to assign tract codes to 1,761 of the projects missing geography data.[13] That left us with a final sample of 29,870 LIHTC projects placed in service between 1987 and 2007. These projects represent approximately 1.8 million units. About 55% of the projects (and units) were new construction, while most of the remainder of the developments were rehabilitations.[14] Projects are located in about 2,600 counties and 16,000 tracts, and just over one fourth (29%) of all projects and units are located in QCTs.

Aggregating up from tract-level information, we calculate for each year between 2000 and 2007 the number and characteristics of LIHTC units, the share of each county's population and land area in QCTs, and the number and share of persons and land area in each county that are in tracts that change status in any given year. Our measure of LIHTC units is a stock, but in the county fixed effect models we describe in the next section, our identification will come from changes in the number of units within counties between 2000 and 2007. Table 1 provides descriptive statistics for the sample that forms the basis for our empirical analysis. The average county has about 36 (sd = 35) LIHTC units per ten thousand residents, and on average, five (sd = 16) LIHTC units per ten thousand county residents are located in QCTs. In counties with a least one QCT, there are an average of 45 (sd=41) LIHTC units per ten thousand residents, 12 of which (sd= 25) are located in QCTs. As we describe below, we use the share of the county's population living in QCTs as an instrument for neighborhood revitalization. The average share of a county's population in a QCT over the sample period was 8%.[15] Notably, about 70% of counties contained no QCTs in 2000, a percentage that fell to 61% by 2007 owing to changes in the formulas and data used to determine qualified status. Meanwhile, about 0.4% of counties were entirely composed of QCTs in 2000, a percentage that rose to 1.3% by 2007. Ranked by their share of the county's overall population in QCTs in 2007, the top 50 counties were home to half the total QCT population but only 27% of the total U.S. population.

[13] Several projects are located at "scattered" or "various" sites; since they could not be precisely geocoded, they were dropped from the sample. The main results were robust to restricting the sample to only those observations for which HUD provided tract information.

[14] About 10% of projects and units were a mix of new construction and rehabilitation or an existing development.

[15] As a robustness check, we consider the share of the county's area in a QCT as an alternative instrument (see Section V.C.). The average share of a county's area in a QCT over the sample period was 6%.

4.2. Uniform Crime Reports

We measure crime using the Uniform Crime Reports County-Level Detailed Arrest and Offense Data (UCRC). These data are based on the Federal Bureau of Investigation's Uniform Crime Reports: Offenses Known and Clearances by Arrest data, but unlike the frequently used agency-specific Uniform Crime Reports (UCR), these data are not official FBI statistics. Instead, the UCRC are created by the staff of the Inter-University Consortium for Political and Social Research (ICPSR) in conjunction with the FBI.

While the UCR is intended to be a census of all crimes known to police in a given year, in practice, roughly 80% of agencies report data to the FBI. In order to generate more accurate county-level crime information for researchers, the ICPSR imputes the annual number of offenses known to police in each county to construct the UCRC. These files are also updated by the ICPSR, so the data may not match the FBI's "Crime in the United States" publications. However, for the purposes of county-level analysis, the UCRC is a more comprehensive than the UCR. In addition, the UCRC contains a "coverage indicator" variable for each observation, which ranges from 0 to 100 and essentially reflects the inverse of the amount of imputation done by the ICPSR; the mean value of this variable is 90. In analysis, we restrict the sample to county/years in which the coverage indicator is larger than 50, such that the average coverage indicator is 97.8 (sd = 6.7).

We focus on a county-level crime for two reasons. First, the aggregation from census tract to county is more straightforward than aggregation from census tract to police jurisdiction. The cost of this aggregation is that our dependent variable will contain crimes occurring in wealthier areas. While not all crime in a county occurs in QCTs, because these areas are the lowest income areas in a county, they tend to be disproportionately represented in the county crime rate.[16] Second, ethnographic research in Chicago suggests that the revitalization of public housing simply displaces individuals prone to criminality to surrounding neighborhoods (Venkatesh 2006). Quantitative research has found that the extent of geographic displacement of crime is small, at most only a few blocks (Di Tella and Schargrodsky 2004). Our county-level analysis allows us to

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[16] For example, Glaeser and Sacerdote (1999) attribute almost all of the relationship between city size and crime to the concentration of female-headed households in large cities, rather than other "big city" features like population density and a lack of social ties.

estimate the effect of locally targeted policy on overall crime rates, explicitly incorporating any potential spatial displacement of crime.

After sharp declines in the late 1990s, crime rates between 2000 and 2006 were relatively stable, with some slight increase in violent crime rates in 2007. Table 1 provides some descriptive statistics on crime rates in our sample. There are an average of 27 (sd = 26) violent crimes and 234 (sd = 149) property crimes per ten thousand residents in our sample. The most common violent crime is aggravated assault; there were an average of 20 (sd = 20) aggravated assaults per ten thousand people in our sample. Other violent crimes, including murders, rapes, and robberies, are much less common, each with fewer than five per ten thousand people on average.[17] The most common property crime is larceny, with an average of 160 (sd = 106) offenses per ten thousand people. Burglaries, motor vehicle theft, and arson, the other main types of property crime, are less common, with 56, 17, and two reported offenses per ten thousand people on average, respectively.

Unlike survey data on victimization, such as the National Crime Victimization Survey, the UCRC only contains crimes that are reported to police and are confirmed by the police as having actually occurred. This means that crime in the UCRC is actually a composite variable equal to

Crime(Share of Crimes Reported to Police)*(Share of Reports Reported by Police to FBI)*

The difference between crime in the UCRC and actual crime is non-trivial; roughly 60% of crimes were not reported to the police in 2006. From a research standpoint, this level difference is less important than systematic variation in reporting by either crime victims or police. Reporting bias in the UCR, and thus the UCRC, has been shown to vary by crime type and be negatively related to the number of local police (Levitt 1998), and crime victims appear to be highly sensitive to changes in the cost of reporting (Owens and Matsudaira 2010). Police officers have openly spoken about manipulating their UCR reports in order to affect their eligibility for federal funding (Maltz 1999). As a result, regression analysis of any policy variable that might

[17] The mean county violent crime rates reported in the table, particularly murder, are an order of magnitude lower than the national crime rate. This is due to a large number of sparsely populated counties with low violent crime rates. For example, in a given year, there are no murders in over 1,700 counties. Only 12% of the U.S. population lives in one of these counties, so these low-crime, low-population areas have little effect on the total number of crimes per capita in the U.S.

alter the probability that a victim reports crime to the police or affects the police department's incentives to report crime to the FBI will not produce unbiased estimates of the relationship between the policy in question and crime; at best, researchers can sign the direction of the bias. This is potentially important for the current analysis, as offenses against abandoned or decrepit property are likely to be systematically underreported relative to crimes involving new construction or recently refurbished property.[18]

5. Identification

We take advantage of adjustments in the formula as well as changes over time in the data and boundaries used to determine QCT status to identify the effect of neighborhood revitalization on criminal activity. Given the large tax advantages of siting new development in a QCT, one tract that just meets the thresholds for qualification would be expected to receive more investment than another that just fails to meet the thresholds but that is otherwise observationally equivalent. Hence, we use an instrumental variables approach that addresses the endogeneity that would otherwise exist between housing quality and crime.[19]

While we have more detailed information on the locations of low-income housing development, our crime data are reliable only at the county level. Hence, we calculate the share of population in a county that resides within QCTs as a measure of housing development in blighted neighborhoods. Again, these shares change over time due to both changes in the formula used to determine QCT status as well as changes in metropolitan area definitions and updates to the census data on which the designations are based. As we discuss in the robustness section, estimates using an alternate area-based measure are qualitatively and quantitatively similar.

We begin with analysis of the relationship between crime rates and community revitalization, controlling for other characteristics of the local area. Our basic specification is

$$CrimeRate_{it} = \alpha + \theta LIH_{it}^{QCT} + \mathbf{X}_{it}\boldsymbol{\beta} + \eta_t + \varepsilon_i \tag{1}$$

[18] This point is emphasized by Cook and MacDonald (2010).

[19] As discussed in Section III, developers who site in DDAs are also eligible to receive a 30% boost in their qualified basis. To the extent that we do not account for DDAs in our IV strategy, it will tend to weaken the first-stage. We are currently working to geographically code DDAs and incorporate them into the analysis.

where $CrimeRate_{it}$ is the number of crimes per ten thousand residents in county i in year t, LIH_{it}^{QCT} is the number of low-income rental units in QCT areas per ten thousand residents in county i in year t, $\mathbf{X}_{it}$ is a vector of county i characteristics, η_t is a dummy for year t, and ε_{it} is the error term. We include in **X** the county share black, share of the population age 15-24, the poverty rate, log median household income, and log population. In this and all regressions that follow, we adjust the standard errors for heteroskedasticity and clustering at the county level.[20]

In some specifications, we also control for "churn" in QCT status by including in **X** the fraction of the county population living in tracts that gained QCT status as well as the fraction of the population that lost QCT status in each year. Controlling for churn in this way allows us to disentangle the effect of QCT status from underlying trends in gentrification. To illustrate, consider two counties similar to Dallas and Cuyahoga counties (depicted in Figures 1 and 3), each of which currently has about one-fifth of the population in QCTs. One might expect that a county such as Dallas, which had more substantial changes in the tracts designated qualified owing to gentrification in and around the urban core as well as an increasing concentration of low-income households on the fringe of the city, would have different crime trends than a county such as Cuyahoga, which while having about the same overall share of the population in QCTs, has had much less pronounced shifts in the spatial distribution of households and income over time.

Estimates of the relationship between crime and LIHTC units from (1) likely suffer omitted variable bias, as the variables in **X** may fail to control for unmeasured characteristics of counties that affect crime rates and also are correlated with low-income housing development. A regression with county fixed effects can control for time-invariant features of locations that might otherwise give rise to bias:

(2) $$CrimeRate_{it} = \alpha + \theta LIH_{it}^{QCT} + \mathbf{X}_{it}\boldsymbol{\beta} + \mu_i + \eta_t + \varepsilon_i$$

[20] Clustering at the MSA level yields standard errors that are nearly identical to those obtained by clustering at the county level.

where μ_i is a dummy for county i. In this specification, the relationship between low-income housing and crime is identified off changes in low-income housing within counties.

While addressing some of the omitted variable bias, estimates from the fixed effect model will be biased if there are unmeasured changes over time in characteristics at the local level that affect both crime and neighborhood revitalization. Such shocks are at the root of the simultaneity problem that calls for an instrumental variable strategy. As previously discussed, we instrument changes in low-income housing with the share of the population in a county living within QCTs. Given that it is unlikely that residents are aware of QCT status or make decisions regarding criminal behavior based on actual or expected QCT status, it can serve as instrument for changes in low-income housing development in blighted communities. In other words, QCT status likely only affects crime rates through its effects on changes in where low-income housing development occurs. The first-stage and reduced-form regressions, then, are

(3) $$LIH_{it}^{QCT} = \varphi QCT_{it} + \mathbf{X}_{it}\boldsymbol{\beta} + \mu_i + \eta_t + \varepsilon_{it}$$

and

(4) $$CrimeRate_{it} = \gamma QCT_{it} + \mathbf{X}_{it}\boldsymbol{\beta} + \mu_i + \eta_t + v_{it}$$

where QCT_{it} represents the share of the population in county i that is in a QCT in year t. The parameter φ captures the first-stage effect of the QCT share on low-income housing development, controlling for changes in the covariates in **X** and any time-invariant features of counties. The parameter γ captures the reduced-form effect of QCT status on crime rates, adjusting for changes in the same covariates. The IV estimator in this just-identified model is simply the ratio γ/φ.

Our measure of QCT status may be mechanically related to the construction of low-income housing units in QCTs versus other areas. If developers chose sites independently of QCT status, then the larger the fraction of a county covered by QCT, the larger the number of those randomly situated units would be designated as QCT eligible. This mechanical relationship, however, should lead to null results in a reduced-form model of crime as a function of QCT coverage and county fixed effects. Since QCT status only affects the tax incentives of developers, if developers make decisions independently of QCT status, we are aware of no mechanism through which variation in QCT coverage driven by federal rule assignments should be related to county-level crime rates. If, however, developers do strategically locate in QCTs instead of other tracts, a behavior consistent with Eriksen and Rosenthal (2008), Baum-Snow and Marion (2009), and Ellen et al. (2009), then we might expect to see a relationship between QCT coverage and social outcomes like crime.

Based on the theory behind the broken windows hypothesis, it is not clear a priori that different types of housing development would have differential effects on crime; both new construction and rehabilitations may help to improve the physical environment and reduce the appearance of disorder.[21] However, we would expect different effects of neighborhood development on different types of crime. This is especially true if the likelihood of not only committing a crime, but also reporting one is correlated with neighborhood conditions. To the extent that community investment increases the propensity of residents to report crime to the police, we expect that the impact of neighborhood revitalization on crime, as measured in the UCRC, will be biased upwards. We know from the NCVS that, on average, violent crimes are reported more frequently and consistently than property crimes. If the baseline reporting rate is lower for property crimes than for violent crimes, then the magnitude of the upward bias in our estimates will be larger for property crime.

6. Results

6.1. OLS and fixed effect regressions

We first consider naïve regressions. In Table 2, we present results from estimating equation (1), which does not include county fixed effects or correct for the endogeneity of low-income housing development. The estimated coefficients on low-income housing units per capita are

[21] To the extent that vacancy rates are high in subsidized units, it could counteract any beneficial effect stemming from the construction or rehabilitation of low-income housing. Information on vacancy rates of properties in our sample is not available. However, Abt Associates (2000) examined a sample of 39 properties in 1999 and found that the average vacancy rate was only 4%. They note that "the relatively low vacancy rates are consistent with the notion that the LIHTC properties represent newer and more desirable housing relative to the overall stock of affordable units" (page 40).

positive and precisely estimated in the regression for every type of crime, although of moderate magnitude. For example, one additional LIHTC unit per ten thousand residents in QCTs within a county is associated with a 0.2 increase in the county-level violent crime rate. A one unit increase in LIHTC units per ten thousand residents in QCTs within a county is associated with an increase in the number of property crimes per capita of about 0.9, which when compared to mean values, corresponds to an elasticity of crime with respect to low-income housing of about 2%. The results are nearly identical whether we control for churn in census tracts entering and exiting QCT status within the county. The positive conditional correlation of crime and low-income housing development in these regressions is not surprising; these specifications do not control for many characteristics of counties that might be positively correlated with both low-income housing and criminal activity. We expect such omitted variables to bias the estimated coefficients on low-income housing development upward.

Indeed, once we include county fixed effects and estimate equation (2), the relationship between low-income housing development and crime rates essentially disappears. These fixed effect estimates are shown in Table 3. In contrast to the previous results without county fixed effects, several of the estimated coefficients are negative, and most are statistically insignificant at conventional levels of precision. Even those that are significant imply relatively small effects; the elasticity of motor vehicle thefts with respect to QCT units, for example, is 1.3%. In sum, while there is a strong positive correlation between low-income housing and county-level crime rates, once we look at within-county variation in development, the existence of any relationship is unclear.

One interpretation of these results is that the average treatment effect of construction in QCTs on crime is zero, as variation in low-income housing development in QCTs is, on average, correlated with other factors that are related to crime rates. What may not be zero is the impact of variation in construction of low-income housing that is plausibly orthogonal to these omitted variables. In order to determine this local average treatment effect, we will focus on changes in low-income housing development that is driven by changes in requirements for QCT status.

Since QCT status is determined by poverty rates and median income, counties with more QCTs will be poorer than other counties, ceteris paribus. Similarly, changes in QCT status will in part reflect economic decline or revitalization. As the results in Tables 2 and 3 reveal, county-level poverty rates are positively related to all violent crimes save rape as well as all property crimes save larceny and arson. Increases in median income are also associated with declines in all crimes except motor vehicle theft. In our fixed effect models, however, we only exploit variation in QCT coverage that is driven by changes in the formulas and boundaries used by HUD, not variation in QCT coverage arising from changes in county characteristics.

6.2. Instrumental variable regressions

Changes in the stock of low-income housing are unlikely to be determined independently of crime rates. Unobserved local shocks that affect crime rates and low-income housing development could bias our fixed effect estimates. Hence, we instrument low-income housing development with the share of the population in a county that is within a QCT. In later robustness checks, we instrument development with the share of the land area in a county within a QCT. Variation in both measures within counties over our sample period is driven by the change in the formula used determine QCT status in 2002, the incorporation of 2000 census data in 2003, and the redefinitions of MSA boundaries in 2004 and 2007.

6.2.1. First-stage results

As we show in Table 4, the fraction of the population that is in a QCT is a strong predictor of low-income housing development. Based on our point estimates in column (1), a 10% increase in the fraction of the population located in a QCT is associated with a 1% increase in the number of low-income housing units in QCTs per ten thousand county residents. As the results in column (2) show, comparing counties with similar "churn" in QCT status increases the magnitude of the relationship between QCT status and QCT housing by over 60%. This reflects the fact that counties where a large number of tracts recently received qualified status will not have any development yet (reflected in the negative and statistically significant coefficient on the "population entering" coefficient), and that low-income housing that was constructed in a formerly qualified tract is still counted in our total county-level stock of QCT units (the relationship between population formerly in a QCT and QCT units is positive). Note that while the coefficients on our population entering and population exiting measures are similar in magnitude to our instrument, the average values of these variables are substantially smaller – 12% and 7% of the size, respectively.

The finding that QCTs attract a disproportionate amount of LIHTC development is consistent with Baum-Snow and Marion (2009), who find that on average in the 1990s, tracts just above the qualification threshold received about six more units (on a base of seven) than tracts just below the threshold. Baum-Snow and Marion also show that QCTs are not only the sites of a larger number of actual LIHTC units, but also attract more initial applications from developers, suggesting that it not just state housing agencies cherry-picking developments that results in observed patterns of construction and rehabilitation.

In column (3) of Table 4, we estimate the impact of changes in the fraction of the population in a QCT on all low-income housing development in a county and find a positive relationship. However, the estimated coefficient is smaller than the standard error. Also, the magnitude of the estimated relationship is small, corresponding to an elasticity of approximately 0.4%. In column (4), we see that increases in the fraction of the county's QCT population are associated with reductions the number of low-income housing units in wealthier (non-QCT) areas. Though we cannot pin down the precise magnitude of the crowd-out effect in this county-level analysis, our results are consistent with past studies showing that development in QCTs crowds out development outside QCTs (Eriksen and Rosenthal 2008, Baum-Snow and Marion 2009). While changes in QCT coverage does not appear to increase development overall, it does appear to increase the probability that low income housing is built in poor neighborhoods within the county.

In the final column of Table 4, we present results of a validity check on our instrument. As previously discussed, there is a mechanical positive correlation between our instrument and our endogenous variable. As the fraction of a county that is a QCT increases, so does the probability that any randomly sited housing complex will be located in a QCT. In this case, variation in QCT status would not be attracting development; rather, it would simply be relabeling pre-existing development plans. In order to disentangle these two effects, we re-ran our first stage using counterfactual QCTs. To create the counterfactuals, we first randomly ranked census tracts within counties each year. Then, based on these rankings, we sequentially assigned qualified status to tracts until the county population living in one of these falsified QCTs was greater than or equal to the value of our true instrument. Next, we identified the number LIHTC projects in each county that were located in falsified QCTs each year. Finally, we aggregated both the fraction of the population living in a falsified QCT and the number of LIHTC projects in falsified QCTs to the county-year level. The results in column (5) of Table 4, in which we use these counterfactual measures of population and projects in QCTs, show that there is a positive mechanical relationship between the fraction of a county designated as QCT and the number of QCT housing units. This mechanical relationship is less than 1/7th the size of our first stage using the true QCTs, and is not statistically different from zero. While not definitive evidence, this supports our assertion that QCT status attracts new development instead of merely reclassifying projects that would have been built anyway.

6.2.2. Reduced-form results

We examine the relationship between QCT coverage and violent crime in Table 5.1. Changes in the fraction of county residents living in QCTs do not appear to be related to murder or rape. Robbery and aggravated assault, on the other hand, appear to fall in counties with a growing number of QCT residents; each percentage point increase in the share of county residents in QCTs (a roughly 12% increase) is associated with a 0.3% reduction in both crimes.[22] In order to put these magnitudes in perspective, a 10% increase in the size of the police force will, on average, cause a 13% reduction in robberies and a 9% reduction in assaults (Evans and Owens 2007). Given the direct relationship between police officers and crime, it is not surprising that the impact of expanding the scope of tax incentives for real estate developers produces more modest social change. As expected, when we exclude our controls for underlying churn in QCT status, we find smaller average effects of contemporaneous QCT status on crime, as counties in which a larger fraction of the population recently gained QCT status have higher crime rates than counties with a more stable distribution of QCT areas.

[22] Cook and MacDonald (2010) also find that robberies and assaults fell more so than other crimes in Business Improvement Districts in Los Angeles.

In Table 5.2, we turn to property offenses. We find no substantive relationship between changes in the share of people living in a QCT and changes in property crime. There is a marginally statistically significant *positive* relationship between car theft and QCT population coverage, corresponding to an elasticity of 0.01. New and potentially more affluent residents may be the target of motor vehicle theft, or the reporting of such crime may increase after housing development has occurred (although for insurance reasons, car theft rarely goes unreported). As with violent crimes, the average effects are smaller when we ignore variation in stable and rapidly changing counties.

The sensitivity of our results to controlling for QCT churn warrants careful consideration of the relationship between QCT status, poverty trends, and crime. While federal administrative rules determine changes in QCT designations, they are driven in part by changes in poverty, and to some extent we are simply comparing crime rates in counties with growing poverty to counties with relatively constant or declining poverty. Using the same specifications, we examine the relationship between poverty and crime in more detail in Table 6. In order to facilitate the comparison of poverty and QCT coverage, in this table we re-scale poverty rates to range from 0 to 1, instead of 0 to 100. In panel A, we eliminate all QCT measures, and confirm that in our fixed effects specification, county poverty rates are positively related to crime, and that conditional on poverty, crime rates are generally higher in counties with a higher median income (and greater inequality). In the bottom panel, we include our population based measure of QCT status, along with an interaction between poverty and QCT coverage, in essence allowing for heterogeneity in the impact of low-income housing subsidies in counties just barely qualifying for QCT status, and counties with higher overall poverty rates.

The negative relationship between QCT coverage and crime rates appears to be driven by variation in QCT coverage in poorer counties. Poverty rates are positive correlates of violent crime, and providing tax credits to real estate developers appears to undo this relationship. To interpret the results of panel B in words, consider two hypothetical counties, A and B, with identical poverty rates. If more of county A is designated as qualified, assault and robbery rates in county A would be lower, translating into an overall lower rate of violent crime relative to B. Turning to nonviolent crime, in which there was on average no relationship between QCT coverage and crime rates, we see the same pattern. In counties with higher poverty rates, QCT status appears to mitigate the typically strong positive relationship between economic disadvantage and property crime.

In the short run, gaining QCT status initiates housing construction or rehabilitation in that area. The initiation of development itself may reduce crime by displacing former residents, by signaling to the surrounding community that the neighborhood is transforming, or through enhanced security at construction sites. Displacing crime-prone residents should shift crime from one location to another. Security guards monitoring construction sites will only deter criminals while the development is taking place. After the new housing units become available, crime rates may continue to be lower if residents have become more vigilant or if local police are more likely to patrol the now-revitalized neighborhood.

We attempt to isolate the long-run impacts of QCT status by limiting our sample to two years: 2000 and 2007, in effect estimating a long-run first difference model used in Baum-Snow and Marion (2009). Our point estimates of these long run effects, presented in Table 7, are identical to the year to year changes. The effects are no longer precisely estimated, but this is due to the reduced sample size; multiplying the standard errors obtained in our full sample by $\sqrt{22969/5692}$ essentially replicates the long run standard errors. While this test does not pinpoint the mechanism through which QCT status affects crime, it does suggest that temporary neighborhood changes, such as security guards posted at construction sites, are not driving our results. Instead, incentivizing developers to begin projects in poor neighborhoods appears to have both an immediate and long lasting impact on crime.

6.2.3. IV Results

If we assume that variation in QCT status affects crime rates only because of the induced variation in the location of housing development, we can use QCT coverage as an instrument for neighborhood revitalization. In turn, we can draw some causal inferences with respect to the effect of housing development on crime and thus shed light on the validity of the broken windows hypothesis. Our IV estimates, which appear in Tables 8.1 and 8.2, suggest that, when scaled by population, each new housing unit located in a QCT rather than a wealthier neighborhood reduces the total number of robberies by 0.12 per ten thousand residents, a 3%

reduction. County-wide aggravated assaults fall by approximately 3% for each new unit located in a poor neighborhood. Using cost-of-victimization estimates from Miller et al. (1996), this new unit generates savings of approximately $19,000 per year in terms of reduced violent crime victimization.

This reduction in violent crime should be balanced by an apparent increase in motor vehicle theft associated with neighborhood revitalization. Indeed, our IV estimates in Table 8.2 imply that, while reducing robbery and aggravated assault, building a rental unit in a poorer area is associated with 0.2 additional car thefts per person, an increase of 1.2% over the sample mean. This increased rate of property crime reduces the social value of the unit by $990, meaning that the net impact of the new rental unit on the total cost of crime is roughly $18,000.

To put these figures in perspective, Eriksen and Rosenthal (2008) estimate that each LIHTC unit costs roughly $90,000 a year in tax expenditures, which corresponds to $0.13 in crime reduction per dollar spent on low income housing. Using estimates of the marginal cost of hiring another police officer and the corresponding reduction in crime from Evans and Owens (2007), a dollar spent hiring an additional police officer generates approximately $3.15 dollars of crime reduction.

Ethnographic research suggests that some low-income housing developers, and in particular non-profits, who site in QCTs may couple their investments with other neighborhood initiatives that may reduce crime. The fact that we observe almost complete crowd out of non-QCT LIHTC units as QCT coverage expands suggests that many developers who use these credits are at least partially profit driven, as opposed to having purely philanthropic motives. This is supported by the tract level analysis in Baum-Snow and Marion (2009), who found that, conditional on QCT status, development occurred primarily in census tracts where housing values were already rising. This is interpreted as evidence that developers systematically choose to build or rehabilitate rental housing in gentrifying QCT neighborhoods, as opposed to those QCT neighborhoods that are relatively stagnant or declining. We will address this issue, as well as explore the sensitivity of our results to other modeling variations, in the next section.

6.3. Robustness

6.3.1. Time trends

New LIHTC development may be attracted disproportionately to QCTs, but in particular QCTs in which crime rates are already on a downward trajectory because the neighborhoods are gentrifying. Alternatively, LIHTC development may be targeted at areas in which developers anticipate further deterioration in conditions so as to ensure a sufficient supply of qualified renters.[23] In order to examine whether or not the changes in QCT status we observe are correlated with pre-existing trends in crime or affordable housing development, we estimate a model in which we allow for heterogeneity in year effects across counties of similar sizes and with similar trends in crime and low-income housing development prior to 2002, the first year that our instrument is identified.[24] We follow Evans and Owens (2007) and divide counties into groups based on "pre-treatment" trends and population size. For each county, we estimate a model of crimes per ten thousand residents prior to 2002 on a linear time trend, and then do the same with low-income housing units per ten thousand residents as a dependent variable.[25] Next, we divide counties into quintiles based on their average population, and within each population group divide counties into quintiles based on their crime and housing growth rates. Each county in each population quintile falls into one of 25 crime-housing "cells," and each cell is assigned its own year fixed effect.[26]

When we include these fixed effects in our IV analysis, the impact of neighborhood revitalization on crime is identified off variation in QCT status among counties of similar size, with similar trends in crime, and similar trends in low-income housing construction. The results using population-based measures, which do not change substantively when we use the area-

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[23] Since developers who take advantage of the LIHTC must devote at least 40% of their units to low-income families (and often devote a much greater share owing to the structure of the program), in an attempt to meet their requisite low-income occupancy levels, developers may favor areas in which the number of low-income families is expected to be high (Rosenthal 2008).

[24] Given the length of the sample period, the number of counties, and the generally linear trend in crime rates during this time period, using county-specific time trends overwhelms our data. Using MSA-specific time trends is also problematic since the geographic coverage of MSAs is not universal.

[25] In these regressions, we include only counties whose boundaries do not change over the sample period.

[26] The results are little changed when we use bins of different sizes, such as quartiles or deciles, although cell sizes grow very small as we increase the number of bins.

based measures discussed in the next section, appear in Table 9. The estimates controlling for pre-treatment trends in crime or low-income housing development are very similar to those in Tables 8.1 and 8.2 and once again suggest that violent crimes overall, and robberies and assaults in particular, decline as a result of low-income housing development. Development has the opposite effect on property crimes, but the estimates are statistically indistinguishable from zero in all cases except motor vehicle thefts.

6.3.2. Area-based instrument

Measuring changes in QCT coverage using square miles, as opposed to population, puts more weight on outlying suburban and rural areas in poverty within counties.[27] Nonetheless, results using an area-based measure are quantitatively similarly to those using a population-based measure. Tables A4, A5, and A8 in the Appendix report first-stage, reduced-form, and IV results using the area-based instrument. Echoing the first-stage results from regressions using the population-based measure, the fraction of the county area that is in a QCT is a strong predictor of low-income housing development; a 10% increase in the fraction of land designated as a qualified census tract is associated with just over a half a percent increase in the number of low-income housing units per ten thousand county residents. Comparing counties with similar churn in QCT status increases the magnitude of the relationship between QCT status and QCT housing by almost fifty percent in this case. Again, similar to our findings with the population-based measure, when we estimate the impact of changes in the fraction of county area designated as a QCT on low-income housing development overall, we find no effect, implying that QCT housing crowds out the development of low-income housing in non-QCT areas.

Turning to the reduced form results using an area-based instrument, increases in the fraction of land with QCT status is associated with reductions in robbery, although the impact is smaller than that resulting from increases the fraction of people living in a QCT; a one percentage point increase in QCT area within a county is associated with a 0.24% reduction in robbery. This corresponds to an elasticity of robbery with respect to QCT coverage of -0.015. As with the

[27] For reasons discussed in footnote 29, we have more confidence that the share of a county's population within QCTs is a valid instrument for changes in crime than we do the share of county area in QCTs.

population-based instrument, the area-based instrument has no discernable effect on property crime.

IV regressions using an area-based instrument yield similar estimates of the effect of low-income housing development on violent crime as regressions using a population-based instrument. However, the previously estimated increase in car theft is no longer statistically distinguishable from zero. We tentatively conclude that the increase in car theft is driven by neighborhood revitalization in densely populated areas, and that more rural or suburban redevelopment is less likely to be associated with higher rates of property crime. However, the point estimates from the regressions using the area-based instrument are qualitatively similar to those using the population-based instrument.

6.4. Mechanisms

We cannot distinguish between changes in the composition of individuals living in an area and changes in the behavior of existing residents as explanations for observed changes in crime. However, the broken windows hypothesis itself does not discriminate between these alternative means by which reductions in disorder in a community might affect crime in that place. Nonetheless, understanding the importance of sorting as opposed to changes in resident behavior is of interest from policymaking and policing perspectives.

Baum-Snow and Marion (2009) find that low-income housing development is associated with higher turnover and notable changes in the composition of the population in small geographic areas between 1990 and 2000.[28] Moreover, renters in LIHTC units tend to have higher incomes than households participating in housing voucher programs or who live in public housing (Abt Associates 2000, McClure 2006). A 1997 U.S. Government Accounting Office report on the program revealed that LIHTC tenants who receive no other federal housing subsidies earn 47% of the AMGI on average, just below the 50-60% threshold required for most units set aside by developers.[29] To the extent that new development draws relatively higher-

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[28] Baum-Snow and Marion (2009) find evidence of significant sorting across Census block groups, which generally contain between 600 and 3,000 residents, as well as at even finer levels of geography. On average, there are close to 70 block groups per county in the U.S.

[29] Developers who receive credits must either dedicate at least 20% of their rental units to tenants at or below 50% of the AMGI or dedicate at least 40% of their rental units to tenants with incomes at or below 60% of the AMGI. In

income and less crime-prone people into poor neighborhoods and displaces others who are lower-income and more crime-prone, we would expect crime rates to decline in areas with LIHTC-financed development.

Our empirical results, which rely on county-level changes, suggest that even to the extent that there is spatial sorting of residents, the effects on crime are not zero-sum. Even if less crime-prone people are displacing more crime-prone residents in QCT areas, most residential mobility, and in particular mobility among low-income households, occurs within counties. According to Current Population Survey data, 67% of the renting population age 15 and over who moved between 2006 and 2007 stayed within the same county. Moreover, the probability of moving within as opposed to between counties varies inversely with income; whereas 68% of the renting population with annual income less than $25,000 (approximately 50% of the median household income in 2007 of the U.S.) that moved between 2006 and 2007 stayed within the same county, only 57% of those with annual income $100,000 and over stayed within county.

We further explore the issue of sorting as well as the possibility that the effects we find arise solely because of changes in the denominator of the crime rates by examining migration patterns between counties. As part of its annual county population estimates, the Census Bureau releases components of change, including net migration (although not immigration and emigration separately). Regressions of net migration scaled by lagged population on our population-based measure of QCT coverage controlling for other county characteristics for 2000-2007 yield no significant results.[30] This finding implies that, although it is not unlikely that QCT status and any associated new affordable housing development induce sorting within counties, they are not likely to prompt substantial cross-county migration. While we cannot rule out that there are relatively large offsetting inflows and outflows of residents in areas with more development, it seems more likely that much of the relocation in response to construction and rehabilitation of low-income housing occurs within counties. If that is true, our results indicate that low-income

practice, the vast majority of developers choose the latter option, devoting a larger number of units to higher-income tenants (to whom they can charge higher rents; the cap is calculated as 30% of either 50% or 60% of AMGI depending on the developer's choice).

[30] There is a marginally significant positive relationship between net in-migration scaled by lagged population and the area-based measure of QCT coverage controlling for other county characteristics between 2000 and 2007, which suggests that the area-based instrument may not be exogenous. This is in part why we choose to focus on results using the population-based measure of QCT coverage.

housing development is likely not merely displacing crime, but rather reducing overall crime levels in affected areas.

7. Conclusion

When first articulated in 1982, the broken windows hypothesis attracted significant academic and policy attention. The idea that reducing social disorder in a community by removing graffiti, repairing dilapidated buildings, and reducing litter is an appealing crime control policy; community revitalization benefits all residents, while tough criminal sanctions impose costs on a relatively small criminal population. However, empirical evidence on the broken windows hypothesis is scant. The best identified studies have typically been weaker tests of the theory itself, focusing on populations moving to neighborhoods with less social disorder rather than on communities that experience changes in the level of disorder.

In this paper, we use a plausibly exogenous change in the location of housing development to test the theory that community revitalization can reduce crime rates. The Department of Housing and Urban Development's LIHTC program provides large tax incentives to developers that either rehabilitate or construct rental housing in the poorest neighborhoods. The "poorest" neighborhoods are determined by a formula that incorporates census tract estimates of the poverty rate, median income, and population, as well as the median income and population of the metropolitan statistical area in which the tract is located. In 2002, 2003, 2004, and 2007, changes to this formula, updates to census data, and redefinitions of MSA boundaries changed which neighborhoods HUD considered the "poorest."

We show that low-income housing follows QCT status, and that as the fraction of a county with QCT status increases, violent crime rates fall. Given that our variation in QCT status is driven by arbitrary federal rule changes, we argue that the only mechanism through which changes in coverage could plausibly affect crime is through the impact of new construction in disadvantaged neighborhoods now designated as the "poorest." We estimate that constructing low-income housing in particularly disadvantaged communities, rather than in already gentrified areas, reduces robberies and assaults by 3%. A failure to find a significant change in property crimes is not surprising, as this is consistent with both an increase in the value of committing property crime and an increase in the probability that citizens in revitalized areas contact the police. Because our crime measure is at the county level, we avoid concerns that this new construction merely displaces crime from one neighborhood to the next. While these effects are modest compared to reductions in crime caused by legal sanctions, the social benefit of this crime reduction is an important positive externality of physical community revitalization.

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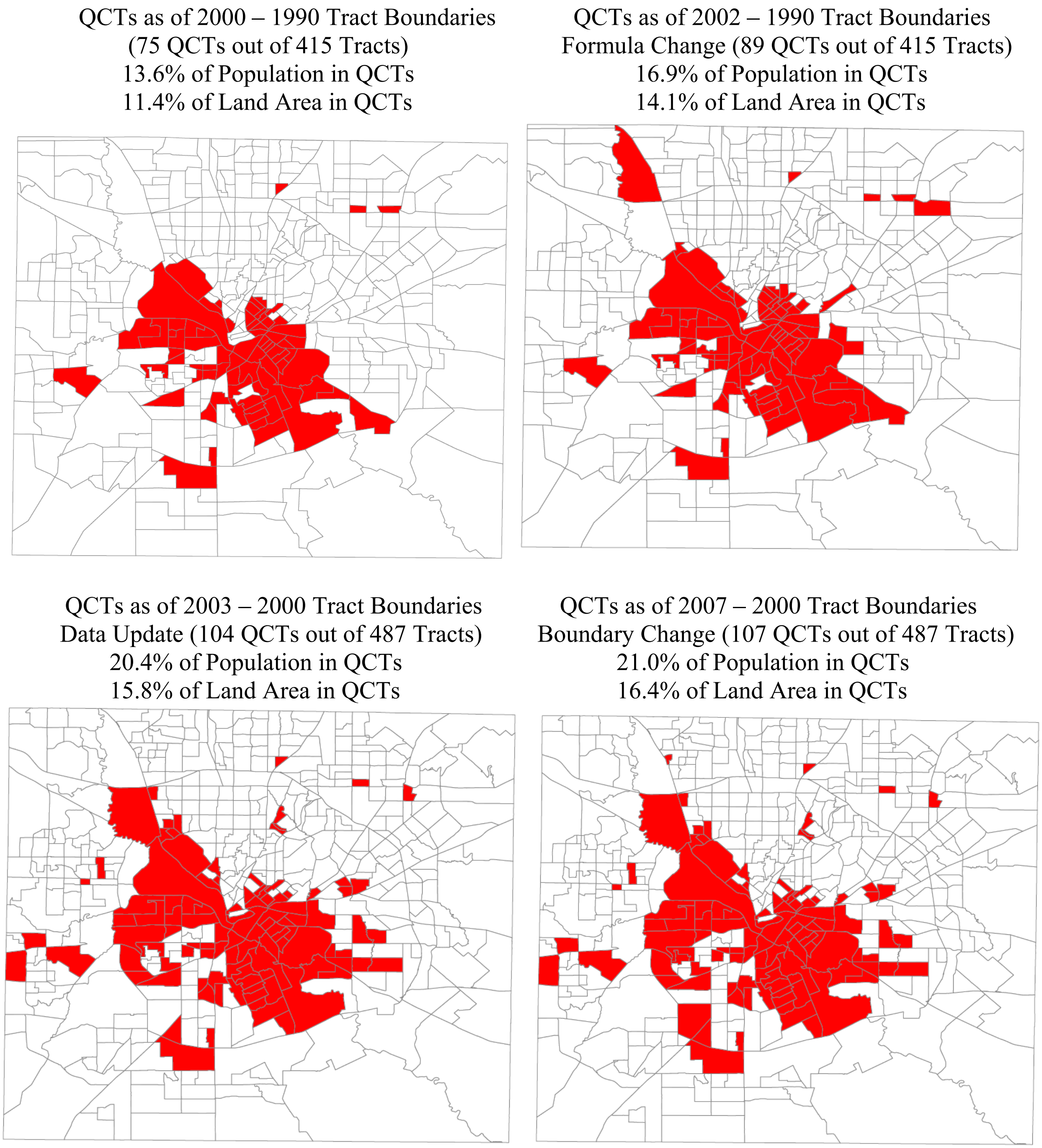
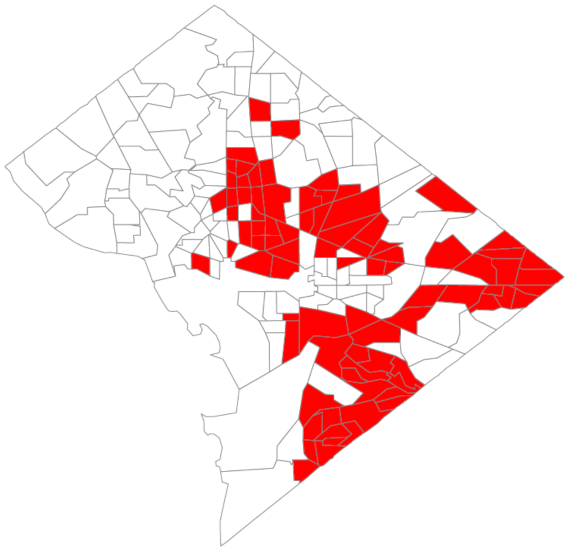
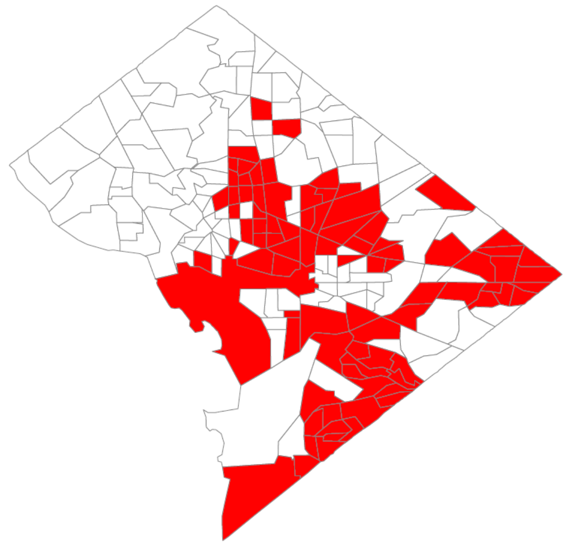


Fig 1. Dallas County (Dallas, Texas).

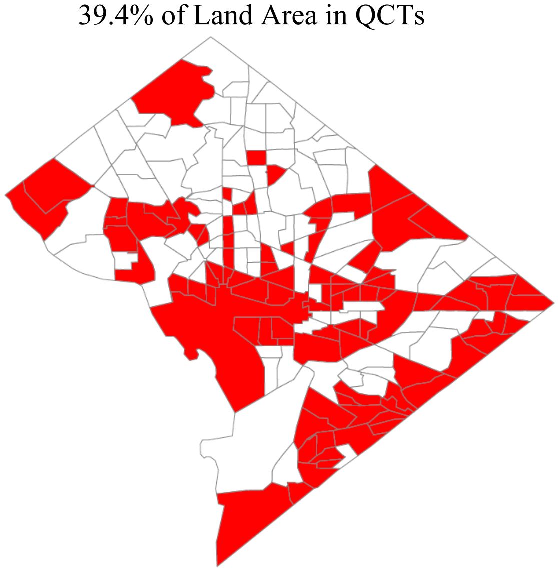
QCTs as of 2000 – 1990 Tract Boundaries
(84 QCTs out of 192 Tracts)
44.5% of Population in QCTs
30.3% of Land Area in QCTs



QCTs as of 2002 – 1990 Tract Boundaries
Formula Change (87 QCTs out of 192 Tracts)
44.6% of Population in QCTs
36.2% of Land Area in QCTs



QCTs as of 2003 – 2000 Tract Boundaries
Data Update (94 QCTs out of 188 Tracts)
49.1% of Population in QCTs
39.4% of Land Area in QCTs



QCTs as of 2007 – 2000 Tract Boundaries
Boundary Change (97 QCTs out of 188 Tracts)
51.2% of Population in QCTs
40.2% of Land Area in QCTs

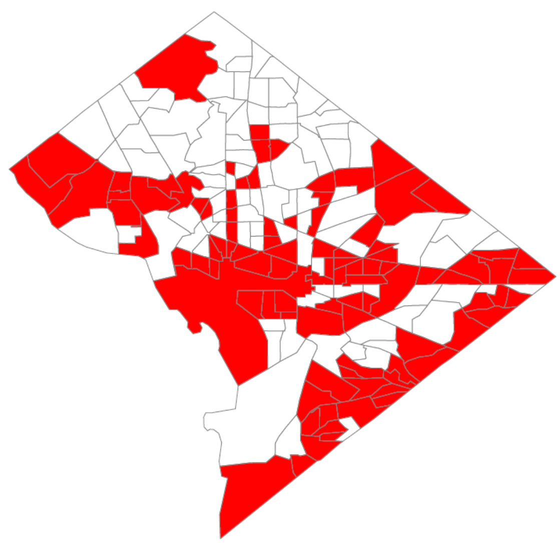
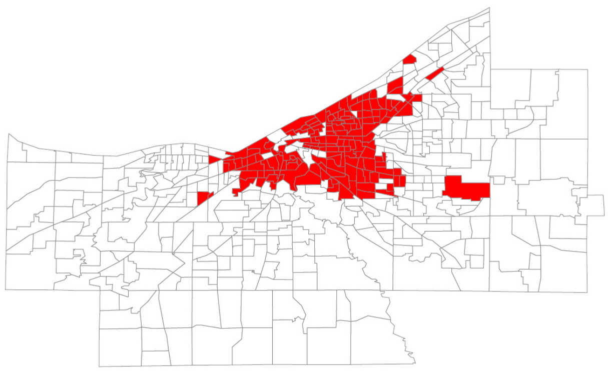
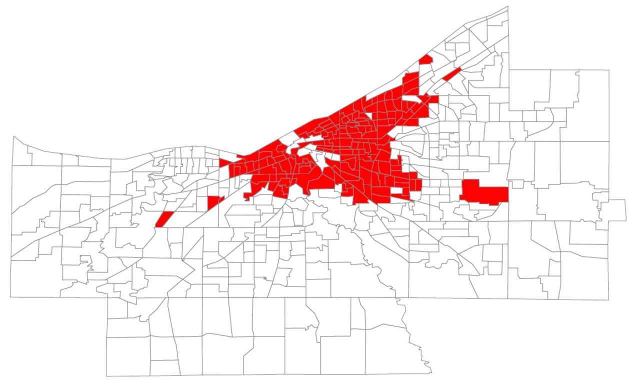


Fig 2. Washington, DC

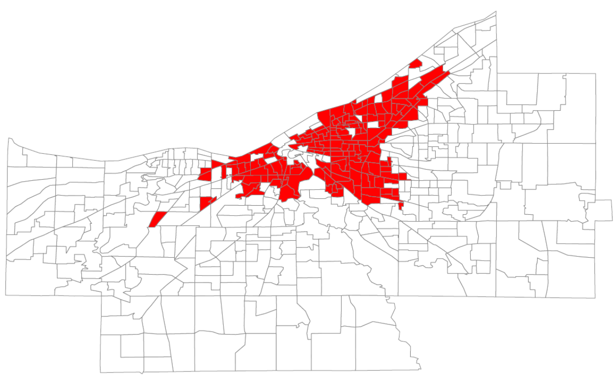
QCTs as of 2000 – 1990 Tract Boundaries
(153 QCTs out of 495 Tracts)
22.2% of Population in QCTs
9.4% of Land Area in QCTs



QCTs as of 2002 – 1990 Tract Boundaries
Formula Change (163 QCTs out of 495 Tracts)
23.9% of Population in QCTs
10.1% of Land Area in QCTs



QCTs as of 2003 – 2000 Tract Boundaries
Data Update (159 QCTs out of 502 Tracts)
21.8% of Population in QCTs
9.2% of Land Area in QCTs



QCTs as of 2007 – 2000 Tract Boundaries
Boundary Change (163 QCTs out of 502 Tracts)
22.6% of Population in QCTs
9.5% of Land Area in QCTs

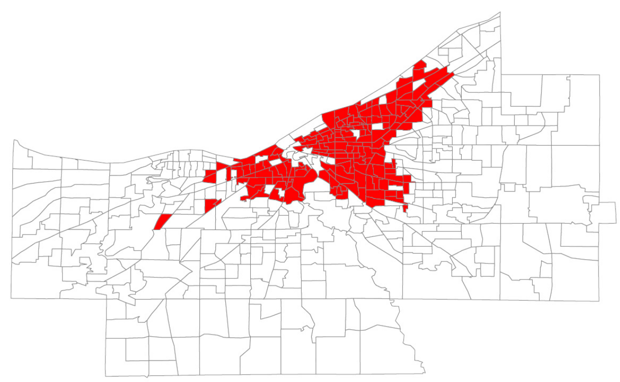


Fig 3. Cuyahoga County (Cleveland, Ohio)

Table 1
Low-income housing, Qualified Census Tracts and crime, 2000-2007

	Mean	Standard Deviation	Minimum	Maximum
Housing Measures				
QCT Units per 10,000	4.74	16.60	0	511.99
LIHTC Units per 10,000	35.91	35.11	0	650.31
Share Population in QCT	0.084	0.17	0	1
Population Entering a QCT	0.012	0.07	0	1
Population Exiting a QCT	0.006	0.05	0	1
Share Area in QCT	0.06	0.17	0	1
Crime Measures				
Total Crimes per 10,000	261.56	166.92	0	3,818.18
Violent Crimes per 10,000	27.25	25.67	0	809.92
Murders per 10,000	0.35	0.69	0	24.10
Rapes per 10,000	2.45	2.44	0	73.59
Robberies per 10,000	4.10	7.00	0	140.02
Assault per 10,000	20.36	20.45	0	808.93
Property Crimes per 10,000	234.31	148.92	0	3,636.36
Burglary per 10,000	55.94	37.93	0	909.09
Larceny per 10,000	159.82	106.29	0	2,363.64
MV Theft per 10,000	16.86	17.90	0	343.81
Arson per 10,000	1.69	2.44	0	181.82
Demographic Measures				
County Poverty Rate	14.12	5.73	1.70	55.90
Ln(County Median Income)	10.58	0.24	9.69	11.58
Ln(County Population)	10.30	1.44	3.81	16.11
Share Black	0.09	0.14	0	0.86
Share Age 15-24	0.14	0.03	0.05	0.49
Observations		22,969		

Notes: Housing and crime measure per 10,000 county residents.

Table 2
OLS estimates of crime and low-income housing.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Burglaries	MV Thefts	Larceny	Arson	Property Crimes	Murders	Rapes	Robberies	Assaults	Violent Crimes
QCT Units Rate	0.100+	0.201**	0.620**	0.00566*	0.927**	0.00350**	0.00683**	0.0907**	0.0514*	0.152**
	[0.0532]	[0.0559]	[0.123]	[0.00267]	[0.209]	[0.00106]	[0.00240]	[0.0200]	[0.0246]	[0.0430]
	47.36**	15.15**	77.40**	-0.207	139.7**	1.084**	0.115	16.86**	28.25**	46.31**
Share Black	[5.799]	[3.276]	[15.37]	[0.285]	[21.93]	[0.0777]	[0.253]	[1.229]	[3.424]	[4.277]
	-43.15**	-37.91**	292.0**	-0.407	210.5**	-1.050**	6.533**	-10.09**	-31.14**	-35.76**
Share Age	[13.39]	[6.142]	[50.11]	[0.751]	[63.07]	[0.143]	[1.001]	[2.503]	[6.853]	[8.701]
15-24	0.462+	0.224+	-0.781	0.021	-0.0746	0.00561*	-0.00943	-0.0819*	0.746**	0.660**
Poverty Rate	[0.253]	[0.119]	[0.690]	[0.0173]	[1.001]	[0.00264]	[0.0180]	[0.0368]	[0.138]	[0.171]
	-34.30**	0.127	-35.73+	-0.223	-70.13*	-0.152*	-0.644	-2.890**	-0.753	-4.439
Log Median	[6.440]	[3.116]	[18.88]	[0.495]	[27.31]	[0.0591]	[0.530]	[0.902]	[3.503]	[4.384]
HH Income	11.15**	6.004**	36.00**	0.313**	53.46**	0.0434**	0.416**	2.433**	3.375**	6.268**
Log Population	[0.697]	[0.387]	[2.006]	[0.0560]	[2.920]	[0.00726]	[0.0422]	[0.119]	[0.341]	[0.432]
	0.100+	0.201**	0.620**	0.00566*	0.927**	0.00350**	0.00683**	0.0907**	0.0514*	0.152**
R-Squared	0.25	0.34	0.30	0.04	0.33	0.11	0.07	0.51	0.18	0.29
Observations	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969
F-Statistic	61.72	44.77	95.06	14.27	94.53	33.72	40.18	71.05	56.36	79.39

Notes: All specifications include 7 year dummies. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets. Significant at +10%; *5%; **1%.

Table 3
Fixed effects estimates of crime and low-income housing.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Burglaries	MV Thefts	Larceny	Arson	Property Crimes	Murders	Rapes	Robberies	Assaults	Violent Crimes
QCT Units Rate	0.0214	-0.0455+	-0.200+	-0.00608+	-0.231	0.000466	0.000284	0.0104	-0.0345	-0.0234
	[0.0380]	[0.0240]	[0.106]	[0.00366]	[0.141]	[0.000885]	[0.00298]	[0.00684]	[0.0225]	[0.0268]
Share Black	87.65	-9.611	-218.9*	-1.732	-142.6	1.644	5.336	22.80**	54.56*	84.34**
	[74.79]	[22.85]	[109.6]	[4.262]	[166.6]	[1.108]	[3.468]	[6.099]	[22.11]	[25.09]
Share Age 15-24	16.53	73.76	438.1	11.92	540.3	0.724	7.129	2.264	-29.91	-19.79
	[94.02]	[66.38]	[308.6]	[19.97]	[482.8]	[1.101]	[4.621]	[2.887]	[22.70]	[22.30]
Poverty Rate	0.147	0.119	1.354+	0.0526	1.671	0.00971+	0.0156	-0.0165	-0.114	-0.105
	[0.218]	[0.129]	[0.744]	[0.0354]	[1.073]	[0.00567]	[0.0167]	[0.0168]	[0.0888]	[0.0961]
Log Median HH Income	-2.764	-0.82	4.54	0.607	1.562	0.124	0.221	0.603	1.311	2.259
	[4.920]	[2.098]	[13.96]	[0.589]	[17.68]	[0.198]	[0.629]	[0.585]	[3.001]	[3.327]
Log Population	-26.30**	-0.245	-60.31**	-0.876	-87.73**	-0.0914	-0.109	0.417	-8.090+	-7.874+
	[9.380]	[3.489]	[15.59]	[0.554]	[25.08]	[0.197]	[0.429]	[0.535]	[4.359]	[4.523]
R-Squared	0.83	0.89	0.88	0.44	0.89	0.31	0.58	0.93	0.80	0.85
Observations	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969
F-Statistic	8.766	9.602	17.02	2.792	15.95	1.374	3.61	9.117	3.106	3.401

Notes: All specifications include 7 year dummies and county fixed effects. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets. Significant at +10%; *5%; **1%.

Table 4
Location of low-income housing and Qualified Census Tract coverage (first stage).

	(1)	(2)	(3)	(4)	(5)
	QCT Units		LIHTC Units	Non-QCT Units	Falsified QCTs
Pop. in QCTs	5.646**	9.130**	2.384	-6.746**	1.219
	[1.096]	[1.762]	[3.076]	[2.590]	[2.058]
Pop. Entering QCTs		-7.617**	-0.8	6.818**	1.195
		[1.582]	[2.459]	[1.937]	[2.169]
Pop. Exiting QCTs		2.162**	4.133**	1.971+	3.594**
		[0.517]	[1.272]	[1.144]	[0.693]
Share Black	-33.06	-32.07	-89.52+	-57.45	-14.36
	[25.23]	[25.22]	[47.54]	[37.85]	[16.63]
Share Age 15-24	-65.86*	-60.87*	-139.3**	-78.47**	-29.48*
	[27.79]	[27.57]	[34.72]	[23.28]	[14.27]
Poverty Rate	0.343**	0.332**	0.548**	0.216**	0.263**
	[0.0690]	[0.0683]	[0.103]	[0.0771]	[0.0524]
Log Median HH	3.072	2.146	-1.594	-3.74	2.471
Income	[2.408]	[2.368]	[4.026]	[3.118]	[1.580]
Log Population	1.067	2.293	9.315+	7.022+	-2.045
	[2.651]	[2.655]	[5.363]	[4.147]	[1.623]
R-Squared	0.90	0.90	0.94	0.94	0.918
Observations	22,969	22,969	22,969	22,969	22,971
F-Statistic	22.57	19.91	84.21	72.79	13.26

Notes: Dependent variables are scaled by county population. All specifications include 7 year dummies and county fixed effects. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets. Significant at +10%; *5%; **1%.

Table 5.1
Qualified Census Tract coverage and violent crimes (reduced form).

	(1)	(2)	(3)	(4)	(5)	(6)
	Murders	Rapes	Robberies	Assaults	Violent Crimes	Violent Crimes
Pop. in QCTs	0.108	0.0676	-1.095**	-5.104+	-6.023+	-3.05
	[0.0970]	[0.242]	[0.421]	[2.911]	[3.128]	[2.164]
Pop. Entering QCTs	-0.0507	-0.156	0.953**	5.791*	6.537*	
	[0.115]	[0.241]	[0.357]	[2.685]	[2.915]	
Pop. Exiting QCTs	0.0282	0.195	-0.248	-1.477	-1.501	
	[0.206]	[0.308]	[0.435]	[1.640]	[1.919]	
Share Black	1.672	5.345	22.02**	53.95*	82.98**	83.82**
	[1.112]	[3.469]	[6.122]	[22.11]	[25.10]	[25.12]
Share Age 15-24	0.782	7.206	0.465	-32.97	-24.52	-20.25
	[1.102]	[4.624]	[2.930]	[22.56]	[22.09]	[22.22]
Poverty Rate	0.00985+	0.0161	-0.0116	-0.117	-0.103	-0.113
	[0.00565]	[0.0168]	[0.0169]	[0.0893]	[0.0964]	[0.0963]
Log Median HH Income	0.122	0.205	0.727	1.833	2.887	2.086
	[0.198]	[0.631]	[0.586]	[3.017]	[3.343]	[3.309]
Log Population	-0.0688	-0.0841	0.154	-9.440*	-9.439*	-8.392+
	[0.198]	[0.439]	[0.529]	[4.372]	[4.525]	[4.521]
R-Squared	0.307	0.582	0.932	0.802	0.854	0.854
Observations	22,969	22,969	22,969	22,969	22,969	22,969
F-Statistic	1.31	3.26	8.11	2.74	3.05	3.43

Notes: All specifications include 7 year dummies and county fixed effects. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets. Significant at +10%; *5%; **1%.

Table 5.2
Qualified Census Tract coverage and property crimes (reduced form).

	(1)	(2)	(3)	(4)	(5)	(6)
	Burglaries	MV Thefts	Arson	Larceny	Property Crimes	Property Crimes
Pop. in QCTs	0.943	1.852+	0.263	2.677	5.734	3.222
	[3.345]	[1.090]	[0.264]	[7.149]	[10.01]	[6.739]
Pop. Entering QCTs	0.224	-1.602	0.123	-7.911	-9.166	
	[3.017]	[1.206]	[0.526]	[5.981]	[7.973]	
Pop. Exiting QCTs	0.53	-2.008+	-0.463+	-4.901	-6.842	
	[3.401]	[1.038]	[0.273]	[7.352]	[10.22]	
Share Black	87.35	-7.324	-1.433	-211.0+	-132.4	-133.0
	[74.89]	[23.32]	[4.289]	[110.8]	[168.2]	[168.3]
Share Age 15-24	15.5	78.92	12.69	455.7	562.8	558.6
	[94.11]	[66.33]	[19.96]	[308.3]	[482.5]	[482.3]
Poverty Rate	0.156	0.0926	0.0498	1.244+	1.543	1.593
	[0.220]	[0.130]	[0.0356]	[0.753]	[1.085]	[1.079]
Log Median HH Income	-2.591	-1.2	0.535	3.226	-0.0301	1.01
	[4.953]	[2.115]	[0.592]	[14.00]	[17.76]	[17.77]
Log Population	-26.18**	0.22	-0.794	-59.51**	-86.27**	-87.21**
	[9.453]	[3.545]	[0.564]	[15.72]	[25.24]	[25.13]
R-Squared	0.825	0.887	0.435	0.884	0.889	0.889
Observations	22,969	22,969	22,969	22,969	22,969	22,969
F-Statistic	7.60	9.07	2.32	14.75	13.88	15.74

Notes: All specifications include 7 year dummies and county fixed effects. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets. Significant at +10%; *5%; **1%.

Table 6

Poverty, Qualified Census Tract coverage, and crime.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Murders	Rapes	Robberies	Assaults	Violent Crimes	Burglaries	MV Thefts	Larceny	Arson	Property Crimes
					Panel A					
Poverty Rate / 100	0.987+	1.57	-1.29	-12.6	-11.3	15.3	10.3	128.7+	5.03	159.4
	[0.563]	[1.66]	[1.69]	[8.90]	[9.64]	[21.9]	[13.0]	[74.7]	[3.56]	[107.8]
Log Median HH Income	0.125	0.213	0.629	1.184	2.15	-2.785	-0.984	3.456	0.569	0.255
	[0.197]	[0.628]	[0.585]	[2.998]	[3.324]	[4.923]	[2.111]	[14.00]	[0.590]	[17.74]
Log Population	-0.0907	-0.0954	0.421	-8.043+	-7.808+	-26.14**	-0.21	-59.63**	-0.847	-86.83**
	[0.197]	[0.428]	[0.529]	[4.343]	[4.508]	[9.369]	[3.493]	[15.61]	[0.555]	[25.05]
Share Black	1.626	5.303	22.42**	55.71*	85.06**	86.63	-8.058	-213.3+	-1.565	-136.3
	[1.111]	[3.470]	[6.137]	[22.19]	[25.20]	[74.78]	[23.36]	[111.0]	[4.296]	[168.4]
Share Age 15-24	0.692	7.123	1.552	-27.46	-18.1	15.22	77	454.1	12.38	558.7
	[1.096]	[4.626]	[2.906]	[22.70]	[22.29]	[93.90]	[66.12]	[307.5]	[19.91]	[481.3]
R-Squared	0.307	0.582	0.932	0.801	0.854	0.825	0.887	0.884	0.435	0.889
					Panel B					
Pop. in QCTs	0.144	0.217	1.703	5.455	7.519	17.45*	8.232**	-0.303	39.75*	65.13*
	[0.222]	[0.809]	[1.054]	[4.681]	[4.838]	[7.145]	[2.998]	[0.795]	[17.98]	[25.43]
Pop. in QCTs x Poverty Rate / 100	-0.267	-1.01	-10.4+	-35.0+	-46.7*	-72.0*	-31.7*	1.56	-171.5*	-273.6*
	[0.936]	[3.46]	[5.48]	[20.2]	[21.0]	[30.7]	[12.5]	[3.38]	[78.4]	[110.8]
Poverty Rate / 100	1.06+	1.84	1.42	-3.49	0.82	34.1	18.6	4.64	173.1*	230.4+
	[0.640]	[1.68]	[1.75]	[9.15]	[10.2]	[24.4]	[15.2]	[3.98]	[86.1]	[124.3]
Log Median HH Income	0.132	0.235	0.747	1.584	2.697	-1.721	-0.5	0.571	6.237	4.587
	[0.200]	[0.630]	[0.580]	[2.975]	[3.308]	[4.989]	[2.091]	[0.603]	[14.37]	[18.23]
Log Population	-0.079	-0.118	0.235	-8.751*	-8.714+	-26.60**	-0.29	-0.857	-61.35**	-89.09**
	[0.198]	[0.435]	[0.533]	[4.351]	[4.507]	[9.391]	[3.502]	[0.560]	[15.60]	[25.02]
Share Black	1.662	5.309	22.03**	54.31*	83.31**	86.63	-7.869	-1.476	-213.2+	-135.9
	[1.111]	[3.470]	[6.127]	[22.12]	[25.08]	[75.13]	[23.36]	[4.304]	[111.0]	[168.8]
Share Age 15-24	0.754	7.122	1.309	-28.45	-19.26	17.36	78.32	12.35	456.3	564.4
	[1.097]	[4.622]	[2.920]	[22.59]	[22.16]	[93.75]	[66.20]	[19.99]	[308.1]	[481.9]
R-Squared	0.307	0.582	0.932	0.801	0.854	0.825	0.888	0.435	0.884	0.889

Notes: All specifications include 7 year dummies, county fixed effects, and 22,969 observations. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets. Significant at +10%; *5%; **1%.

Table 7

Change in Qualified Census Tract coverage and crime, 2000 and 2007.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Murders	Rapes	Robberies	Assaults	Violent Crimes	Burglaries	MV Thefts	Larceny	Arson	Property Crimes
Pop. in QCTs	0.178	0.302	-1.151	-8.658	-9.329	6.164	3.205	0.322	12.09	21.78
	[0.369]	[0.600]	[0.838]	[5.887]	[6.317]	[6.910]	[2.029]	[0.609]	[15.54]	[21.13]
Pop. Entering QCTs	1.223	0.397	-0.716	0.316	1.22	37.51	6.046	0.351	19.8	63.71
	[1.257]	[1.441]	[3.227]	[13.02]	[15.51]	[35.37]	[8.226]	[1.316]	[74.99]	[99.86]
Pop. Exiting QCTs	0.257	-3.083	-6.652	-42.93	-52.4	18.03	-20.3	0.531	-28.05	-29.78
	[2.035]	[2.070]	[5.243]	[34.18]	[37.36]	[28.90]	[14.58]	[2.295]	[97.34]	[124.2]
Poverty Rate	-1.7E-05	0.0494	0.0314	0.0934	0.174	0.848	0.0453	0.148	2.371	3.411
	[0.0176]	[0.0548]	[0.0461]	[0.319]	[0.331]	[0.645]	[0.202]	[0.130]	[1.707]	[2.418]
Log Median HH Income	0.235	-0.143	0.299	3.775	4.166	-6.221	-0.677	-0.357	-18.77	-26.03
	[0.617]	[1.709]	[1.612]	[9.093]	[9.834]	[14.47]	[5.694]	[2.003]	[39.21]	[51.33]
Log Population	-0.179	-0.317	0.287	-5.499	-5.708	-14.09	0.953	-1.25	-47.55*	-61.94*
	[0.327]	[0.802]	[0.723]	[5.031]	[5.397]	[9.359]	[3.271]	[1.322]	[18.82]	[25.33]
Share Black	2.988	0.891	24.45*	34.65	62.98+	56.38	-20.5	-4.86	-299.1+	-268
	[2.028]	[4.133]	[9.550]	[33.55]	[37.76]	[101.8]	[30.90]	[9.906]	[174.0]	[262.1]
Share Age 15-24	0.0391	9.245	-6.473	-5.427	-2.616	47.7	71.1	39.73	756.4	914.9
	[2.908]	[10.05]	[6.224]	[78.83]	[78.78]	[232.2]	[69.06]	[66.56]	[760.3]	[1116.1]
R-Squared	0.615	0.69	0.96	0.846	0.889	0.866	0.903	0.579	0.886	0.891
Observations	5692	5692	5692	5692	5692	5692	5692	5692	5692	5692
F-Statistic	0.808	1.083	4.25	0.717	0.907	1.297	0.896	0.818	6.344	4.321

Notes: All specifications include county fixed effects and one year dummy. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets. Significant at +10%; *5%; **1%.

Table 8.1
Location of low-income housing and violent crimes (IV).

	(1)	(2)	(3)	(4)	(5)
	Murders	Rapes	Robberies	Assaults	Violent Crimes
QCT Units Rate	0.0118	0.00741	-0.120*	-0.559+	-0.660*
	[0.0103]	[0.0246]	[0.0482]	[0.308]	[0.335]
Pop. Entering QCTs	0.0391	-0.1	0.0393	1.533	1.512
	[0.0859]	[0.177]	[0.296]	[1.375]	[1.493]
Pop. Exiting QCTs	0.00272	0.179	0.0118	-0.268	-0.0748
	[0.193]	[0.288]	[0.401]	[1.562]	[1.826]
Share Black	2.050+	5.582+	18.17**	36.02	61.82*
	[1.125]	[3.350]	[6.559]	[25.02]	[28.53]
Share Age 15-24	1.5	7.657+	-6.835	-67.01*	-64.69*
	[1.278]	[4.595]	[5.102]	[30.97]	[32.66]
Poverty Rate	0.00593	0.0136	0.0283	0.0687	0.116
	[0.00605]	[0.0180]	[0.0212]	[0.143]	[0.155]
Log Median HH Income	0.097	0.189	0.984	3.035	4.305
	[0.187]	[0.592]	[0.601]	[3.187]	[3.542]
Log Population	-0.0958	-0.101	0.429	-8.159+	-7.928+
	[0.177]	[0.400]	[0.547]	[4.322]	[4.563]
Observations	22,962	22,962	22,962	22,962	22,962
F-Statistic	1.35	3.746	8.481	2.887	3.197

Notes: All specifications include 7 year dummies and county fixed effects. 7 observations not contributing to identification (one observation per county) are excluded. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets. Significant at +10%; *5%; **1%.

Table 8.2

Location of low-income housing and property crimes (IV).

	(1)	(3)	(5)	(7)	(9)
	Burglaries	MV Thefts	Arson	Larceny	Property Crimes
QCT Units Rate	0.103	0.203+	0.0288	0.293	0.628
	[0.343]	[0.119]	[0.0281]	[0.732]	[1.033]
Pop. Entering QCTs	1.317	-0.463	-0.244	-2.668	-2.058
	[2.161]	[0.682]	[0.198]	[3.833]	[5.575]
Pop. Exiting QCTs	0.000357	-2.040+	0.0611	-8.545	-10.52
	[2.795]	[1.057]	[0.485]	[5.405]	[7.225]
Share Black	90.67	-0.819	-0.51	-201.6+	-112.2
	[71.24]	[23.35]	[4.215]	[105.6]	[160.8]
Share Age 15-24	21.79	91.27	14.44	473.6	601.1
	[91.87]	[63.63]	[19.03]	[296.6]	[462.6]
Poverty Rate	0.122	0.0252	0.0402	1.147	1.334
	[0.231]	[0.122]	[0.0323]	[0.706]	[1.018]
Log Median HH Income	-2.813	-1.635	0.473	2.596	-1.38
	[4.706]	[2.091]	[0.564]	[13.04]	[16.67]
Log Population	-26.42**	-0.244	-0.86	-60.18**	-87.70**
	[8.699]	[3.363]	[0.533]	[14.64]	[23.42]
Observations	22,962	22,962	22,962	22,962	22,962
F-Statistic	8.748	10.18	2.559	16.85	15.8

Notes: All specifications include 7 year dummies and county fixed effects. 7 observations not contributing to identification (one observation per county) are excluded. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets. Significant at +10%; *5%; **1%.

Table 9

Location of low-income housing and crimes, group-specific fixed effects (IV).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Murders	Rapes	Robberies	Assaults	Violent Crimes	Burglaries	Motor Vehicle Thefts	Arson	Larceny	Property Crimes
QCT Units Rate	0.0150	0.00504	-0.123**	-0.475+	-0.579+	0.191	0.232*	0.0334	0.556	1.012
	[0.0111]	[0.0247]	[0.0467]	[0.284]	[0.306]	[0.335]	[0.105]	[0.0287]	[0.741]	[1.048]
Pop. Entering QCTs	0.0516	0.0766	-0.0141	2.468+	2.582	1.776	0.375	-0.0377	2.24	4.352
	[0.0965]	[0.205]	[0.342]	[1.499]	[1.625]	[2.331]	[0.703]	[0.220]	[4.072]	[5.879]
Pop. Exiting QCTs	0.088	0.266	-0.357	-2.638+	-2.641	-2.583	-1.749+	-0.0294	-8.24	-12.6
	[0.216]	[0.315]	[0.405]	[1.511]	[1.815]	[2.862]	[0.948]	[0.554]	[5.745]	[7.672]
Share Black	1.982	7.948*	15.87*	35.65	61.46+	90.88	15.86	3.092	-75.03	34.8
	[1.274]	[3.549]	[7.158]	[31.06]	[35.33]	[67.53]	[24.50]	[3.897]	[109.6]	[160.2]
Share Age 15-24	1.900	5.903	-4.168	-27.99	-24.36	62.39	94.21	18.25	555.3	730.1
	[1.313]	[4.395]	[5.050]	[27.04]	[29.23]	[104.5]	[73.03]	[22.15]	[341.6]	[535.3]
Poverty Rate	0.00612	0.0126	0.026	-0.114	-0.0694	-0.0356	-0.00476	0.0498	0.838	0.848
	[0.00608]	[0.0206]	[0.0202]	[0.131]	[0.140]	[0.230]	[0.130]	[0.0339]	[0.751]	[1.076]
Log Median HH Income	0.107	0.102	0.968	1.105	2.282	-4.629	-3.238	0.298	-2.907	-10.48
	[0.202]	[0.645]	[0.623]	[3.284]	[3.653]	[4.828]	[2.235]	[0.557]	[13.05]	[16.73]
Log Population	-0.352	0.338	-2.116*	-24.60**	-26.73**	-39.77**	4.279	-0.675	-63.97**	-100.1**
	[0.274]	[0.647]	[1.077]	[7.144]	[7.454]	[9.023]	[3.708]	[0.850]	[18.09]	[24.38]
Observations	21451	21451	21451	21451	21451	21451	21451	21451	21451	21451
F-Statistic	142.7	28.42	6.813	7557.9	12.82	25.08	190.9	10.26	236.3	49.92

Notes: All specifications include county fixed effects and poverty and housing trend quintile-specific year fixed effects. 1,518 observations not contributing to identification (collinear with group-specific fixed effects) are excluded. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets. Significant at +10%; *5%; **1%.

Appendix

Table A4
Location of low-income housing and Qualified Census Tract coverage: area-based measures (first stage).

	(1)	(2)	(3)	(4)
	QCT Units		LIHTC Units	Non-QCT Units
Area in QCTs	4.276*	7.284**	-0.563	-7.847*
	[1.730]	[2.665]	[4.592]	[3.911]
Area Entering QCTs		-6.409**	1.613	8.022**
		[2.126]	[3.588]	[3.037]
Area Exiting QCTs		1.129*	2.668*	1.539
		[0.564]	[1.306]	[1.153]
Share Black	-33.52	-32.48	-90.77+	-58.29
	[25.13]	[25.06]	[47.27]	[37.73]
Share Age 15-24	-67.89*	-65.10*	-141.7**	-76.62**
	[27.40]	[26.67]	[34.31]	[23.24]
Poverty Rate	0.346**	0.338**	0.549**	0.211**
	[0.0693]	[0.0695]	[0.104]	[0.0774]
Log Median HH Income	3.149	2.448	-1.375	-3.823
	[2.370]	[2.421]	[4.051]	[3.120]
Log Population	0.628	1.484	8.624	7.140+
	[2.761]	[2.897]	[5.429]	[4.074]
R-Squared	0.90	0.90	0.94	0.94
Observations	22,969	22,969	22,969	22,969
F-Statistic	22.83	19.97	84.42	72.69

Notes: Dependent variables are scaled by county population. All specifications include 7 year dummies and county fixed effects. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets. Significant at +10%; *5%; **1%.

Table A5.1
Qualified Census Tract coverage and violent crimes: area-based measures (reduced form).

	(1)	(2)	(3)	(4)	(5)
	Murders	Rapes	Robberies	Assaults	Violent Crimes
Area in QCTs	0.055	0.102	-0.907*	-4.201	-4.951+
	[0.0968]	[0.257]	[0.367]	[2.611]	[2.785]
Area Entering QCTs	-0.0556	-0.308	0.710*	6.071*	6.417*
	[0.124]	[0.260]	[0.341]	[2.636]	[2.867]
Area Exiting QCTs	0.106	0.0732	-0.124	-0.339	-0.284
	[0.166]	[0.246]	[0.381]	[1.703]	[1.879]
Share Black	1.648	5.355	22.04**	54.14*	83.18**
	[1.113]	[3.472]	[6.128]	[22.04]	[25.03]
Share Age 15-24	0.731	7.226	0.984	-30.7	-21.76
	[1.099]	[4.630]	[2.940]	[22.68]	[22.25]
Poverty Rate	0.0102+	0.0154	-0.0125	-0.117	-0.104
	[0.00561]	[0.0168]	[0.0169]	[0.0890]	[0.0962]
Log Median HH Income	0.123	0.186	0.675	1.804	2.787
	[0.197]	[0.632]	[0.587]	[3.013]	[3.340]
Log Population	-0.0804	-0.0734	0.254	-9.069*	-8.968*
	[0.198]	[0.437]	[0.535]	[4.371]	[4.530]
R-Squared	0.307	0.582	0.932	0.802	0.854
Observations	22,969	22,969	22,969	22,969	22,969
F-Statistic	1.26	3.368	8.097	2.69	2.991

Notes: All specifications include 7 year dummies and county fixed effects. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets. Significant at +10%; *5%; **1%.

Table A5.2
Qualified Census Tract coverage and property crimes: area-based measures (reduced form).

	(1)	(2)	(3)	(4)	(5)
	Burglaries	MV Thefts	Arson	Larceny	Property Crimes
Area in QCTs	-0.641	2.115	0.227	1.629	3.33
	[3.531]	[1.483]	[0.264]	[7.231]	[10.32]
Area Entering QCTs	-0.143	-0.778	0.109	-9.541+	-10.35
	[3.160]	[1.434]	[0.400]	[5.793]	[8.272]
Area Exiting QCTs	-0.109	-2.188+	-0.512+	-4.757	-7.567
	[3.765]	[1.292]	[0.285]	[8.117]	[11.43]
Share Black	86.59	-7.085	-1.44	-211.0+	-133
	[74.74]	[23.30]	[4.293]	[110.8]	[168.0]
Share Age 15-24	14.79	78.32	12.57	453.5	559.2
	[94.02]	[66.24]	[19.93]	[308.0]	[482.0]
Poverty Rate	0.153	0.0967	0.05	1.237	1.536
	[0.221]	[0.131]	[0.0357]	[0.754]	[1.088]
Log Median HH Income	-2.762	-1.144	0.533	3.205	-0.167
	[4.963]	[2.111]	[0.592]	[14.06]	[17.83]
Log Population	-26.37**	0.175	-0.81	-59.76**	-86.76**
	[9.551]	[3.612]	[0.560]	[15.89]	[25.62]
R-Squared	0.825	0.887	0.435	0.884	0.889
Observations	22,969	22,969	22,969	22,969	22,969
F-Statistic	7.617	9.041	2.365	14.78	13.80

Notes: All specifications include 7 year dummies and county fixed effects. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets. Significant at +10%; *5%; **1%.

Table A8.1
Location of low-income housing and violent crimes: area-based measures (IV).

	(1)	(2)	(3)	(4)	(5)
	Murders	Rapes	Robberies	Assaults	Violent Crimes
QCT Units Rate	0.00755	0.014	-0.125*	-0.577	-0.680+
	[0.0128]	[0.0329]	[0.0609]	[0.374]	[0.409]
Area Entering QCTs	0.0972	0.0574	0.0166	0.312	0.483
	[0.155]	[0.228]	[0.357]	[1.563]	[1.755]
Area Exiting QCTs	-0.00723	-0.218	-0.0886	2.375	2.061
	[0.0983]	[0.169]	[0.283]	[1.457]	[1.592]
Share Black	1.893+	5.811+	18.00**	35.4	61.10*
	[1.140]	[3.466]	[6.588]	[25.17]	[28.67]
Share Age 15-24	1.223	8.139+	-7.126	-68.25*	-66.02*
	[1.359]	[4.904]	[4.787]	[32.23]	[33.26]
Poverty Rate	0.00766	0.0107	0.0296	0.0783	0.126
	[0.00646]	[0.0191]	[0.0261]	[0.165]	[0.181]
Log Median HH Income	-0.0916	-0.0942	0.439	-8.213+	-7.959+
	[0.179]	[0.400]	[0.549]	[4.326]	[4.569]
Log Population	0.104	0.151	0.98	3.216	4.452
	[0.187]	[0.594]	[0.634]	[3.361]	[3.745]
Observations	22,962	22,962	22,962	22,962	22,962
F-Statistic	1.41	3.855	8.389	2.814	3.09

Notes: All specifications include 7 year dummies and county fixed effects. 7 observations not contributing to identification (one observation per county) are excluded. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets. Significant at +10%; *5%; **1%.

Table A8.2

Location of low-income housing and property crimes: area-based measures (IV).

	(1)	(2)	(3)	(4)	(5)
	Burglaries	MV Thefts	Arson	Larceny	Property Crimes
QCT Units Rate	-0.0881	0.29	0.0311	0.224	0.457
	[0.451]	[0.216]	[0.0363]	[0.931]	[1.335]
Area Entering QCTs	-0.674	-0.327	-0.313	-3.324	-4.637
	[2.189]	[0.740]	[0.196]	[4.216]	[5.957]
Area Exiting QCTs	-0.0437	-1.106	0.0743	-9.793+	-10.87
	[2.970]	[1.219]	[0.367]	[5.237]	[7.546]
Share Black	83.73	2.348	-0.43	-203.8+	-118.1
	[71.35]	[24.51]	[4.334]	[106.2]	[159.9]
Share Age 15-24	9.053	97.22	14.59	468.1	588.9
	[94.30]	[64.48]	[19.04]	[298.8]	[465.0]
Poverty Rate	0.183	-0.00156	0.0394	1.161	1.382
	[0.253]	[0.138]	[0.0333]	[0.740]	[1.068]
Log Median HH Income	-2.546	-1.855	0.457	2.658	-1.287
	[4.792]	[2.208]	[0.570]	[13.22]	[16.84]
Log Population	-26.24**	-0.256	-0.856	-60.09**	-87.44**
	[8.776]	[3.413]	[0.534]	[14.52]	[23.25]
Observations	22,962	22,962	22,962	22,962	22,962
F-Statistic	8.761	9.919	2.613	16.92	15.79

Notes: All specifications include 7 year dummies and county fixed effects. 7 observations not contributing to identification (one observation per county) are excluded. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets. Significant at +10%; *5%; **1%.