Low-Income Housing Development and Crime

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ABSTRACT

This paper examines the effect of rental housing development subsidized by the federal government's Low-Income Housing Tax Credit (LIHTC) program on local crime. Under the LIHTC program, certain high-poverty census tracts receive Qualified Census Tract (QCT) status, which affects the size of the tax credits developers receive for building low-income housing. Changes in federal rules determining QCT status generate quasi-experimental variation in the location of LIHTC projects. Exploiting this variation, we find that 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.

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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 development may 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. Depending on the extent to which immigrants and emigrants are differentially prone to criminality, this displacement could affect the level and nature of crime in the immediate vicinity of new development, although it may only serve to shift crime from one neighborhood to another. 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 federal government's Low-Income Housing Tax Credit (LIHTC) program on 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 LIHTC steers new low-income housing 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 effect on measured 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 communities is associated with reductions in crime suggests a more nuanced relationship between neighborhood conditions and crime than might be expected in light of well-known results from 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). While the MTO findings may hold at the individual level, our results indicate that improving the quality of housing in the poorest neighborhoods has a net negative impact on aggregate county violent crime rates. Further, our results suggest that shifting the location of new low-income housing toward poorer areas counteracts the persistent positive relationship between poverty and crime. Finally, while only suggestive, we provide some evidence using tract-level data that the reductions in violent crime associated with the program are localized in low-income areas and do not come entirely at the expense of higher crime in surrounding neighborhoods.

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). Subsidizing 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 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 that 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 lots or abandoned buildings 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. Taking advantage of the formula structure of the program in the 1990s, Baum-Snow and Marion (2009) show that not only does the program promote more affordable rental housing construction in low-income neighborhoods, but also that the effects of LIHTC development on communities are heterogeneous. In particular, new development has different impacts on nearby home values and local household income in gentrifying neighborhoods than it does in stable or declining neighborhoods. Meanwhile, 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 versus reducing the cost to low-income residents of moving into higher income areas.

Consistent with past research on other types of place-based subsidized housing (Murray 1999, Sinai and Waldfogel 2005), Baum-Snow and Marion (2009) and Eriksen and Rosenthal (2010) show that LIHTC development crowds out a large fraction of new unsubsidized rental construction. However, using data for projects in California, Eriksen (2009) finds that the LIHTC program encourages development of higher quality units on average. Burge (2011) and Lang (2011), 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.

2.2. Crime and subsidized housing

A large literature in sociology and ethnography has drawn links between subsidized housing and criminal activity (Roncek et al. 1981, Farley 1982, McNulty and Holloway 2000). The results of these studies are mixed, in part because many focus narrowly on a select city and time period, if not a particular housing development or neighborhood. Further, they have largely considered only the effect of public housing projects, many of which have either been demolished or are currently in the process of rehabilitation. 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.[1]

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 local crime by attracting individuals from other neighborhoods who might be more prone to criminal activity. The construction of new affordable

[1] 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.

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 within the project (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.[2] As housing projects age, the deterioration of the physical environment may directly encourage criminal behavior; dilapidated, unkempt structures may signal that more serious criminal behavior is tolerated in an area, or that the probability of being apprehended for unlawful acts is low. This idea is often referred to as the "broken windows hypothesis" (Wilson and Kelling 1982).

Building on this sociological work is a growing literature in economics on how physical infrastructure and income segregation affect crime rates. Multiple studies of the MTO experiment find that randomly assigning people to move to more affluent communities that are typically less disorderly does not result in reductions in individual criminal behavior (Kling et al. 2005, Harcourt and Ludwig 2006, Kling and Ludwig 2007). However, moving an individual to a nicer neighborhood is not the same as improving conditions in a given neighborhood. A smaller number of studies have considered how place-based initiatives that target particular neighborhoods or regions for capital or infrastructure investment affect crime. For example, Cook and Macdonald (2010) find evidence that commercial areas in Los Angeles designated as Business Improvement Districts experienced reductions in aggravated assaults and robberies, which they attribute to increased private investment in crime prevention.

Consistent with both the MTO studies and Cook and Macdonald (2010) is a "crowd in" relationship between investment in infrastructure and crime. Reductions in physical disorder in a particular neighborhood may increase the perceived return to making personal investments in crime reductions. For example, residents may be less likely to prop open doors that have

[2] 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).

functioning locks. Well-lit and safe shared spaces in multi-family buildings may increase knowledge about who does, and does not, belong in a neighborhood.

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 aforementioned research implies that by encouraging the development and rehabilitation of rental housing for low-income families, the LIHTC program may reduce local crime, but also may simply displace crime from one neighborhood to another. To the extent that subsidies under the program, which we describe in detail in the next section, result in more low-income housing development in already poor areas, the LIHTC program may contribute to the concentration of poverty within cities. Past research suggests that concentrated poverty may exacerbate crime problems (Glaeser et al. 1996). In a study closely related to ours, Bjerk (2010) finds that the geographic concentration of the poor within metropolitan areas increases robberies and assaults, but reduces burglaries. Bjerk (2010) is primarily based on a model of defensive and offensive violence, but it is also plausible that by exacerbating spatial mismatch in employment and housing opportunities, poverty concentration may make it difficult for residents of disadvantaged neighborhoods to find legitimate work, and hence increase their optimal participation in crime.

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 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.[4]

[3] The LIHTC program subsidizes the development of affordable housing, whose effects on low-income neighborhoods are arguably of more interest from a policy perspective than the effects of gentrification given the political impracticability of a program that subsidizes gentrification.

[4] There were 38.9 million rental housing units in 2007 according to the American Housing Survey. http://www.census.gov/hhes/www/housing/ahs/ahs07/ahs07.html.

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).[5] State housing agencies have discretion over which projects receive tax credits, but federal law requires states to file Qualified Allocation Plans (QAPs) that document any preferences or set-asides within their tax credit competitions (Gustafson and Walker 2002).

Developers are eligible 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.[6] 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.[7] Prior to 2002, a census tract qualified as a QCT if 50% of its households had incomes below 60% of the AMGI unless the

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[5] 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.

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

[7] 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.

total population of designated QCTs within a metropolitan area exceeds 20% of that 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.

A DDA is a metropolitan area, county (or county equivalent), or census place with high construction, land, and utility costs relative to the AMGI. Projects located in both a QCT and DDA are eligible for only one subsidy increase. However, in all but nine states,[8] developers have an explicit incentive to locate in a QCT in DDAs. Gustafson and Walker (2002) note that nearly all state QAPs explicitly indicate that developers locating in high poverty, extremely low income, or "targeted improvement areas" receive preference in the qualification process. To the extent that developers face uncertainty about whether the state will approve their LIHTC application, locating in a QCT increases the probability of receiving LIHTC credits.

As part of the Community Renewal Tax Relief Act of 2000, Congress added another criterion to determine eligibility of tracts for QCT status. Effective January 1, 2002, a census tract can qualify as a QCT 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%.[9]

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.

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[8] These states are Colorado, Delaware, Florida, Missouri, Mississippi, Oregon, Pennsylvania, Rhode Island, and Vermont. Note that the QAPs from these states do not explicitly state that income or poverty is used in allocating credits, which does not mean that developers in these states do not expect QCTs to be given preference.

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

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, 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. This affects the AMGI with which HUD compares 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 adoption of new metropolitan area definitions.

Figures 1 and 2 show the geographic distribution of QCTs in 2000, 2002, 2003, and 2007 for the counties that encompass Washington, DC and Detroit, Michigan. In Washington, DC, a relatively poor county, 84 of the 192 tracts were designated qualified as of 2000 based on 1990 tract definitions and Decennial Census data). Those 84 tracts were home to 44.5% of the 1990 population and covered 30.3% of the county's land area. The introduction of the poverty criterion for QCT designation in 2002 added three tracts the list of those qualified in the county and resulted in slight increases in the population and land area covered by QCTs in the county (to 44.6% and 36.2%, 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 western part of the county as well as a removal the designation for several gentrified tracts just north of the capital. More minor changes in QCT designations accompanied the changes in MSA boundaries and AMGI announced in 2007. Meanwhile, Wayne County, whose county seat is Detroit, had a more stable distribution of QCTs. With roughly one-third of the population but only one-fifth of the land area designated qualified between 2000 and 2007, Wayne County highlights how in many areas, QCTs tend to be the more densely populated tracts.

4. Data

4.1. Department of Housing and Urban Development

We obtained data on areas qualifying for larger tax credits and on low-income housing developments 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, which together with AMGI, determine QCT status. Data from the 1990 Decennial Census were used by HUD to determine QCT designations prior to 2002, while data from the 2000 Decennial Census were used to determine designations in 2003 and after. For the purposes of robustness tests, we also collected annual information on DDA designations; depending on the state QAP, developers may have less of an incentive to site projects in QCTs that are located inside DDAs.

HUD also publishes 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 include the year each 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 each 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 determined 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,[10] 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, and we were able to assign tract codes to 1,761 of the projects missing geography

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

data.[11] 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.[12] We aggregated the project data to the census tract level and defined a LIHTC unit located in tract *j* in year *t* as being in a QCT if (1) the unit was placed in service when tract *j* was a QCT, and (2) tract *j* is a QCT in year *t*. LIHTC projects are located in about 2,600 counties and 16,000 tracts, and just over one fourth of all projects and units are located in QCTs.

Aggregating up from tract-level information, we calculated for each county and year between 2000 and 2007 the number and characteristics of LIHTC units inside and outside QCTs, the share of the county's population and land area in QCTs, and the share of the county's population and land area that are in tracts that change QCT status. 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 38 (sd = 38) LIHTC units per ten thousand residents, and on average, four (sd = 16) LIHTC units per ten thousand county residents are located in QCTs.[13] 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 8.4%.[14] 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.

[11] 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.

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

[13] Note that while about 29% of all LIHTC units are located in QCTs, a smaller fraction of units per 10,000 people are located in QCTs since QCTs tend to be in denser areas.

[14] As a robustness check, we consider the share of the county's area in a QCT as an alternative instrument (see Section 6.3.2). 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 the analysis, we restrict the sample to county/years in which the coverage indicator is greater than 50, such that the average coverage indicator is 97.8 (sd = 6.7).

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 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.[15] 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

[15] The mean county violent crime rates reported in the table are an order of magnitude lower than the national rates. This is due to a large number of sparsely populated counties with low violent crime rates. For example, there are no murders in about half of all counties in our sample in any given year. However, only about one-eighth of the U.S. population lives in one of these counties, so they have little effect on the national crime rates.

crime, occur less frequently, 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; more than half of crimes were not reported to the police in 2009 (Rand and Truman 2010). 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 to 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 also 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 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.[16]

4.3. Aggregation and the geography of crime

While not without important limitations, we focus on county-level crime for three reasons. First, we will show that within counties, QCTs tend to attract development away from non-QCTs as opposed to increase the total amount of low-income housing. That suggests that, within counties, even tracts that never qualified do not represent suitable controls for tracts with QCT

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

status, as patterns of development in both QCTs and non-QCTs are affected by the federal rule changes we exploit. To the extent that the "broken windows" story of crime is true, and that non-QCTs are less likely to receive LIHTC investment than QCTs, the total impact of a change in QCT coverage may be to decrease crime in QCTs and increase it in non-QCTs. In turn, a tract-level analysis that compares outcomes in QCTs with those in non-QCTs will overstate the impact of new housing on crime rates.

The possibility of residential displacement in the wake of low-income housing development is a second motivation for our aggregated analysis. While the extent to which LIHTC construction displaces existing residents is unclear, in part because of the dearth of information on the tenants of LIHTC housing developments (Ellen et al. 2009), ethnographic research in Chicago suggests that the revitalization of public housing merely displaces individuals prone to criminality to surrounding neighborhoods (Venkatesh 2006). If new development in QCTs displaces criminal residents from the area, it may simply shift crime from affected areas to other parts of the county. On the other hand, if new development in QCTs attracts crime-prone residents from elsewhere in the county, it may increase crime in affected areas but decrease it in neighboring communities. From a policy standpoint, the jurisdiction-level crime rate, rather than the geographic distribution of criminal activity within the jurisdiction, is of first-order importance. A tract-level analysis would confound crime displacement and crime reductions. Our county-level analysis allows us to estimate the net effect of locally targeted policy on overall crime rates, explicitly incorporating any potential spatial displacement of crime.

Finally, there is no national dataset that contains crime at the tract level. Crime statistics are available at such a disaggregated geographic level for a few select cities,[17] but our identification strategy requires a relatively large sample. The UCRC strikes the best possible balance between geographic detail and scope.[18]

The cost of this aggregation is that our dependent variable will contain crimes occurring in wealthier areas. The impact of improvements in the housing stock on behavior may be highly

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[17] Rosenthal and Ross (2010) exploit tract-level crime data from five cities.

[18] Some of the statistical problems with the UCRC, which Maltz (1999) discuss in detail, are not present in the police jurisdiction-level UCR, suggesting that jurisdiction, rather than county, is the appropriate level of aggregation. However, the aggregation from census tract to county is more straightforward than aggregation from census tract to police jurisdiction. The county-level aggregation has the benefit of reducing measurement error in our independent variables, as we would only be able to approximate QCT coverage in police jurisdictions.

localized, as the crime reducing effects of local amenities have been shown to dissipate rapidly over space (Linden and Rockoff 2006, Pope 2008). While it is unlikely that 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.[19] If improving the quality of rental housing in the poorest areas reduces crime in those tracts and does not impact crime anywhere else, then our estimates will be shaded by the contribution of QCTs to overall county crime. For example, if 100% of the crime occurs in one census tract, reducing tract-level crime by 25% will also reduce overall crime by 25%. A 25% crime reduction in a tract that only contributes 10% to the aggregate crime rate will only reduce county-level crime by 2.5%. Without knowing the geographic distribution of crime within counties, we are limited in our ability to assess the magnitude of the resulting bias. However, to the extent that crime is dispersed across many tracts within counties, it will reduce our ability to identify a statistically precise relationship between affordable housing development and crime at the county level.

Further, and perhaps most importantly, we are unable to differentiate between multiple plausible mechanisms relating crime to the location of low-income housing development with a county-level analysis. Glaeser and Sacerdote (1999) review a variety of potential causal links between cities and crime, one of which is the "opportunity hypothesis." High population density implies that urban criminals do not have to travel far to steal valuable items. If QCTs draw low-income housing and crime-prone residents away from wealthier areas, any observed reduction in crime at the county level may be driven by a reduction in crime in non-QCT areas. Alternatively, if opportunity is less important than social disorder as a determinate of crime, or if LIHTC development displaces the most crime prone residents from neighborhoods, improving the stock of rental housing in the poorest, most disordered, census tracts may reduce crime in those neighborhoods. Therefore, identifying the geographic source of any observed changes in crime would help to distinguish between these alternative mechanisms. Later in the paper, using tract-level crime data for two cities, we provide some suggestive evidence pointing to relatively large reductions in violent crime the immediate vicinity of QCTs that is not offset by increases in

[19] 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.

surrounding neighborhoods. However, we leave further investigation of this pattern and the mechanisms behind it to future research.

5. Identification

We take advantage of adjustments in the formula as well as the timing of changes 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.

While we have more detailed information on the locations of low-income housing development, our national crime data are reliable only at the county level. We therefore construct a county-level measure that captures the incentives developers have to build or rehabilitate affordable housing in particular tracts. In particular, we use the share of the population in a county that resides in a QCT in a given year. The decision to locate a new project in a given tract is affected by both the size of the expected tax credit and the availability of suitable sites (vacant lots or distressed properties) where there is also sufficient demand for affordable housing.[20] If only a small fraction of a county is designated qualified, developers may want to locate in a QCT all else being equal, but may be unable to find a suitable site. As QCT coverage increases, however, so does the ability of developers to take advantage of the larger tax credit. Again, QCT coverage changes over time due to both adjustments 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.

We begin with an analysis of the relationship between crime rates and low-income housing development, controlling for other characteristics of the local area. Our basic specification is

[20] We focus on population as opposed to land area because a population-based measure better captures the expected ability of developers to find tenants for subsidized units (Rosenthal 2008). As we discuss in Section 6.3.2, our results are generally robust to using an area-based measure instead of a population-based one.

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

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. Each of these variables is obtained from the U.S. Census Bureau and varies by year.[21] In this and all regressions that follow, we adjust the standard errors for heteroskedasticity and clustering at the county level.[22]

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 and to control for potentially heterogeneous responses of areas with different historical patterns of change in the geographic distribution of households and income, which variation in our instrument will not entirely capture. To illustrate, consider two counties, A and B, that are similar to Washington, DC and Wayne (depicted in Figures 1 and 2), respectively. Suppose that in both counties A and B, the fraction of the population living in a QCT increased from 40% in 2000 to 46% in 2007. Such an increase in QCT coverage could occur with or without substantial changes in the areas designated qualified. For example, suppose that in county A, the increase in QCT coverage between 2000 and 2007 occurred as non-QCT tracts containing 46% of the population gained QCT status, while all of the formerly qualified tracts lost status. Meanwhile, suppose that in county B, the six percentage point increase in QCT coverage was entirely due to one additional census tract gaining QCT designation, while the remainder of tracts merely maintained their previous qualified status. One might expect county A, which more closely resembles Washington, DC in the degree to which it experienced substantial changes in the spatial distribution of households and income and thus in QCTs over time, to have different patterns of low-income

[21] Annual information on county share black, share of the population age 15-24, and population come from the U.S. Census Bureau's Population Estimates Program. Annual poverty rate and median household income data are derived from the Census Bureau's Small Area Income and Poverty Estimates Program.

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

housing development (as well as crime) than county B, which more closely resembles Wayne County in terms of its lack of pronounced shifts in the locations of more and less affluent neighborhoods and in QCTs.

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

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 choose 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 changes should be related to county-level crime rates. If, however, developers do strategically locate in QCTs instead of other tracts, a behavior consistent with 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.

To the extent that new development under the LIHTC program crowds out other private investment in QCT tracts, it would bias us toward finding no effect of LIHTC development on crime. However, to the extent that LIHTC developments would not have occurred in the absence of the program, or that LIHTC development are of higher quality or attract higher-income residents than what would have otherwise been built, we might expect to find an effect on crime rates.

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 of neighborhoods as well as affect the composition of residents.[23] However, we would expect different effects of neighborhood development on different types of crime. This is

[23] 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).

especially true if the likelihood of not only committing a crime, but also reporting one is correlated with neighborhood conditions. In particular, if community investment increases the propensity of residents to report crime to the police, we would expect that the impact of neighborhood revitalization on crime, as measured in the UCRC, would be biased upwards. We know from the National Crime Victimization Survey that, on average, violent crimes are reported more frequently and consistently than property crimes (Rand and Truman 2010). 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 relating LIHTC development in QCTs and crime rates. 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. For each type of crime, the estimated coefficient on low-income housing units per capita is positive and precisely estimated. Further, the magnitudes of the estimated relationships are nontrivial. For example, one additional LIHTC unit in a QCT per ten thousand residents within a county is associated with a 0.2 increase in the county-level violent crime rate, which when compared to mean values, corresponds to an elasticity of about 2%. Meanwhile, a one unit increase in LIHTC units in a QCT per ten thousand residents within a county is associated with an increase in the number of property crimes per capita of about one, which corresponds to an elasticity of property 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 appear 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.[24] Even those that are significant imply relatively small effects; the elasticity of motor vehicle thefts with respect to QCT units, for example, is 0.8%. 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 nature of any such relationship becomes less clear.

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 federal rules and the data used to determine QCT status.

6.2. Instrumental variable regressions

Changes in the location 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 an area currently defined as a QCT. 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. The OLS results suggest that county-level poverty rates tend to be positively related to violent as well as property crimes. Meanwhile, increases in median income are associated with declines in most types of crime. In our fixed effect models and in the IV results that follow, however, we only exploit variation in QCT

[24] Controlling for churn in QCT coverage affects the estimates little; fixed effect estimates including population entering and exiting QCTs are presented in Appendix Table A1.

coverage that is driven by the timing of changes in the formulas and boundaries used by HUD, not variation in QCT coverage arising from continuous changes in county characteristics.

In robustness checks, we incorporate information on DDAs and state QAPs into the analysis. We also conduct the analysis with an alternative instrument based on the share of the land area in a county within a QCT. Variation in both the population-based and the area-based 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 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 LIHTC development in low-income neighborhoods. 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 1.8% increase in the number of low-income housing units in QCTs per ten thousand county residents. Recall that our instrument does not identify the source of the change in QCT coverage. One county with a great deal of gentrification (and thus turnover in QCTs) and another county that has a relatively stagnant spatial distribution of income may experience the same change in the share of the population in QCTs over time. However, we might expect two such counties to have different patterns of LIHTC development. As the results in column (2) show, comparing counties with similar "churn" in QCT status increases the magnitude of the relationship between QCT coverage and QCT housing by about 50%.

We do not find evidence that the estimated effect of QCT coverage on the location of development is driven by states with QAPs that explicitly favor developments in QCTs. As the results in column (3) of Table 4 show, the estimated coefficient on the interaction between QCT coverage and a dummy for a lack of an explicit preference for developments in QCTs in a state's QAP is not statistically distinguishable from zero. However, this may be due to a lack of power; only 6% of counties are in states that do not favor QCTs. In column (4), we also show results using only the subsample of counties in what we deem "QCT preference areas"; that is, counties that are either not DDAs or that are located in states whose QAP gives preference to developments in QCTs. This reduces the sample by 1,381 observations. However, the magnitude and significance of the estimated effect of QCT coverage on housing development is very similar for this subsample, suggesting that the presence of DDAs in areas with no preferential treatment of QCTs in our main sample does not affect our estimates substantially. Notably, in columns (1)-(4), the F-statistics reported at the bottom of the table for the joint significance of the instruments suggest that our instrument is relevant.

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 (5) 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 0.5%. In column (6), 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 QCTs redirecting housing development from more affluent areas to lower income areas within counties. Changes in QCT coverage do not appear to increase development overall, but instead seem 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 a set of 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 (7) 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. Although statistically significant, this mechanical relationship is one-fifth the size of our estimate using the true QCTs. Further, the F-statistic associated with the regression in column (7) is less than four, indicative of a weak instrument. While not definitive evidence, this supports our assertion that QCT status attracts new development to poor areas 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 about a half percent reduction in both crimes.[25] 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. Consistent with our first stage estimates, when we exclude

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

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.

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 0.9%. This could be the result of increased reporting of vehicle theft after housing development has occurred. However, for insurance reasons, car theft rarely goes unreported. Therefore, it seems more likely that new and potentially more affluent residents that appear in the wake of new development may be the target of motor vehicle theft. As with violent crimes, the average effects for property crimes overall are smaller when we ignore variation in stable and rapidly changing counties.[26]

The sensitivity of our results to controlling for QCT churn warrants careful consideration of the relationship between QCT status, poverty, 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 increasing poverty to counties with relatively constant or declining poverty. That being said, QCT coverage is not simply a proxy for county poverty rates. Figure 3 verifies that there is substantial overlap in poverty rates in counties with varying levels of QCT coverage; even though counties with a large share of the population in QCTs (e.g., in the fourth quartile of the QCT coverage distribution) have higher poverty rates on average, there are many counties with lower QCT shares that have equally high poverty rates. It is therefore possible to compare two counties with equal poverty rates but different LIHTC "treatments."

We exploit this variation in QCT coverage across counties with similar poverty rates to examine the relationship between poverty and crime 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

[26] The results are little changed when we exclude DDAs where there is no preference given under state QAPs to low-income areas. Results for this subsample appear in Tables A2 and A3.

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 results in Table 6 suggest that the negative relationship between QCT coverage and crime rates is 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.

The effects of new development on crime might be short-lived, especially if it is merely attributable to enhanced security around construction sites. 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 very similar 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 revitalization of the poorest neighborhoods. In turn, we can draw some causal inferences with respect to the effect of housing development on crime. Our IV estimates for violent crime, which appear in Table 8.1, suggest that housing development in low-income areas spurred by the LIHTC program has a negative and significant effect on robbery and assault rates as well as the overall violent crime rate.[27] In particular, when scaled by population, each new LIHTC unit that is located in a QCT rather than a wealthier neighborhood reduces the total number of robberies by 0.08 per ten thousand residents, a 2% reduction. County-wide aggravated assaults fall by approximately 1.8% 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 $13,100 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, each new unit per ten thousand residents built in poorer areas is associated with 0.14 additional car thefts per ten thousand residents, an increase of 0.8% over the sample mean. This increased rate of property crime reduces the social value of the unit by $600, meaning that the net impact of the new rental unit on the total cost of crime is roughly $12,500.

To put these figures in perspective, estimates from the GAO (2002) and Eriksen and Rosenthal (2010) suggest that each LIHTC unit costs around $12,000 a year in tax expenditures on average (in 2006 dollars). Since about 29% of units are built in QCTs and the tax credit is 30% larger for those units, it costs roughly $2,500 more to place a unit in a qualified tract than in a non-qualified tract. For the sake of comparison, Evans and Owens (2007) estimate that hiring one additional police officer provides a marginal benefit of $96,000 in terms of reduced victimization each year and increases annual police expenditure by $54,000.

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[27] The final columns of Tables 8.1 and 8.2, which limit the sample to QCT preference areas, suggest that the main results are not affected by the presence of DDAs. Further, our results are not driven by differences inside and outside MSAs. For example, when we limit our sample to counties the 2,185 counties in our sample that are not in MSAs, we find that a 10% increase in the population living in a QCT is associated with a 4.7% increase in the number of LIHTC units in QCTs, a 2.1% reduction in assaults, and a 3.9% reduction in robberies. All of these effects are precisely estimated.

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 substantial 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 to 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.[28] 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.[29] 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

[28] 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).

[29] 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.

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 in QCTs per ten thousand residents as a dependent variable.[30] 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.[31]

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 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.[32] Nonetheless, results using an area-based measure are quantitatively similarly to those using a population-based measure. Tables A4, A5.1, A5.2, A6.1, and A6.2 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, regardless of the explicit state preference for locating in a QCT. Comparing counties with similar churn in QCT status again increases the magnitude of the relationship between QCT coverage and QCT housing by almost fifty percent. Also, similar to our findings with the population-based measure, when we estimate the impact of

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

[31] 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.

[32] For reasons discussed in footnote 35, 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.

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 0.22% reduction in robbery. This corresponds to an elasticity of robbery with respect to QCT coverage of -0.013. As with the 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

The data and empirical approach we use in previous sections do not permit us to 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. We also cannot identify the precise geographic sources of observed changes in crime. As previously argued, the net effect of development on crime at the county level may be of greater interest from a policy-making perspective. However, the role of sorting as opposed to changes in resident behavior as well as the underlying spatial patterns of housing development and crime are also of interest. Before turning to a tract-level analysis using data for two cities, we consider the potential importance of household mobility and changing neighborhood composition in explaining the results.

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.[33] 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 Accountability 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.[34] To the extent that new development draws relatively higher-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, but may increase in surrounding areas.

Our estimates capture the total effect of the location of LIHTC development if the areas receiving the displaced residents are located in the same county as the newly qualified tract. 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

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[33] 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.

[34] 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 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).

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.[35] 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 housing development is likely not merely displacing crime across counties, but rather reducing crime levels on net in affected areas. However, it remains to be determined to what extent observed changes in crime at the county level arise because of changes in qualified areas, changes in wealthier areas, or changes in both.

6.5. Tract-level crime patterns

In an effort to shed additional light on the geographic sources of changes in crime within counties, we provide some evidence on the spatial pattern of low-income housing development and changes in crime using case studies of two cities in two time periods. The Seattle Police Department publishes census tract-level crime reports on its website. We also obtained tract-level crime reports from the Washington, DC police department in 2006 and 2007 through a research agreement.

In Figure 4, we plot LIHTC projects and units per 10,000 residents as well as the average change in the violent crime rate and the motor vehicle theft rate between 2001 and 2002 as a function of the distance in kilometers to the nearest QCT in Seattle. During this time period, the percent of King County, Washington residents living in QCTs increased from 16.2% to 19.3%. LIHTC projects and units per capita as well as each crime rate are averaged in QCTs (where the distance equals zero) and within 0.2km bins between the centroids of qualified and non-qualified tracts. The size of the points is proportional to the cumulative population of tracts in each bin.

[35] 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.

Not surprisingly given the incentives to locate in qualified areas, LIHTC projects and units in Seattle are clearly concentrated in QCTs. Meanwhile, violent crime rates in and close to QCTs in Seattle appear to have fallen between 2001 and 2002, whereas motor vehicle thefts exhibited very little clear spatial pattern of change.

In Figure 5, we present similar graphs for Washington, DC between 2006 and 2007, during which time the percent of the DC population living in a QCT increased from 49.1 to 51.2%. Again, there is a strong tendency for projects and units to be concentrated in QCTs. Meanwhile, there is some suggestive evidence that violent crime fell more in tracts closer to QCTs (although violent crime rates were essentially flat in the QCTs themselves). As in Seattle, motor vehicle thefts show less of a clear relationship.

Taken together, these results suggest that reductions in violent crime at the county level may be driven by reductions in lower-income areas that are partially, but not entirely, offset by changes elsewhere in the county. If true, this finding runs counter to the idea that the LIHTC program concentrates poverty and leads to reductions in crime in wealthier areas as opposed to near new developments. The results are more consistent with the idea that, either because of residential sorting or because of changes in residents' behavior, violent crime falls in neighborhoods targeted for low-income housing development.

7. Conclusion

In this paper, we take advantage of plausibly exogenous variation in the location of low-income housing developments to test the theory that investment in the housing stock in distressed communities 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, 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 QCTs, 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 federal rule changes, we argue that the only mechanism through which changes in coverage could plausibly affect crime is through their impact on rental housing development in low-income neighborhoods. We estimate that constructing low-income housing in particularly disadvantaged communities reduces robberies and assaults by about 2%. A failure to find a significant change in property crimes is not surprising, as this is consistent with both an increase in the returns 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, our central results are not driven by displacement of crime from one neighborhood to another. Based on an examination of tract-level data for two select cities, though, it appears as if the observed aggregate reduction in violent crime is driven primarily by reductions in areas that are targeted for investment and that receive more development. While the magnitude of the effects we find are modest compared to reductions in crime caused by legal sanctions, the social benefit of this crime reduction is an important positive externality of investment in the housing stock of distressed communities.

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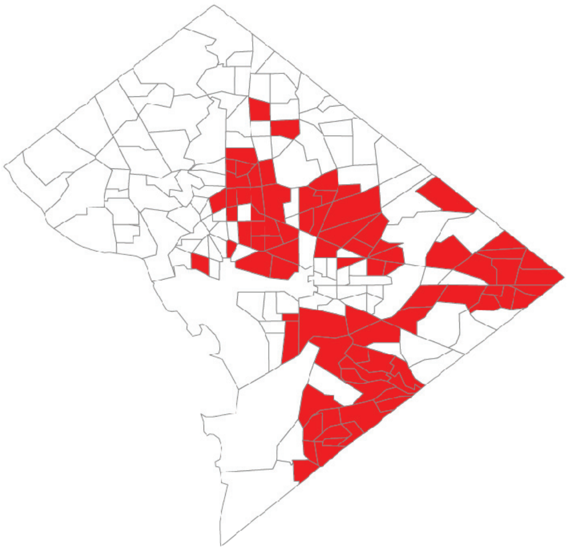
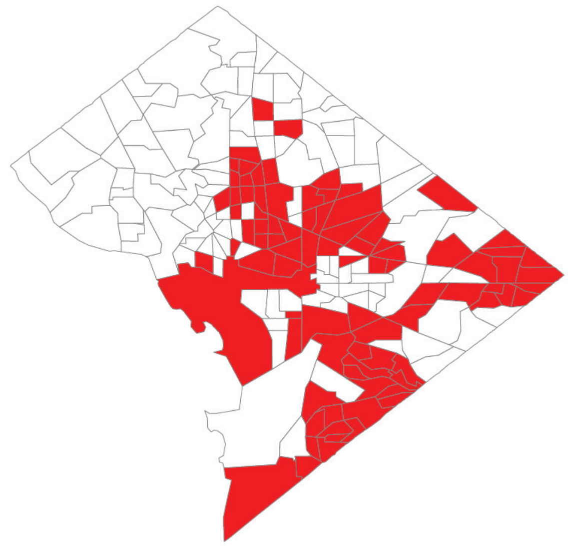
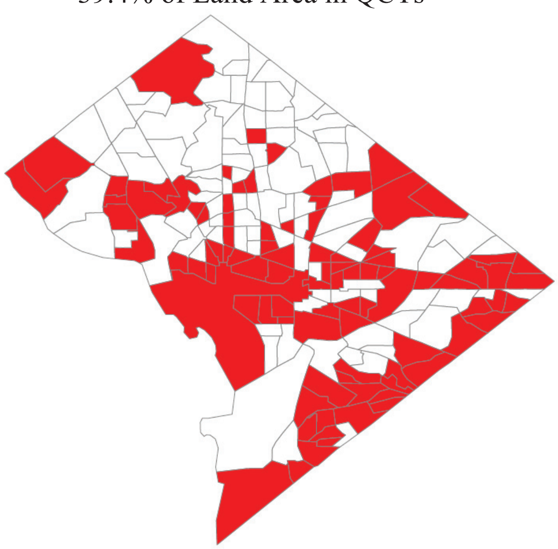
QCTs as of 2000 – 1990 Tract Boundaries
(84 QCTs out of 192 Tracts)
44.5% of Population in QCTs
30.3% of Land Area in QCTs



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

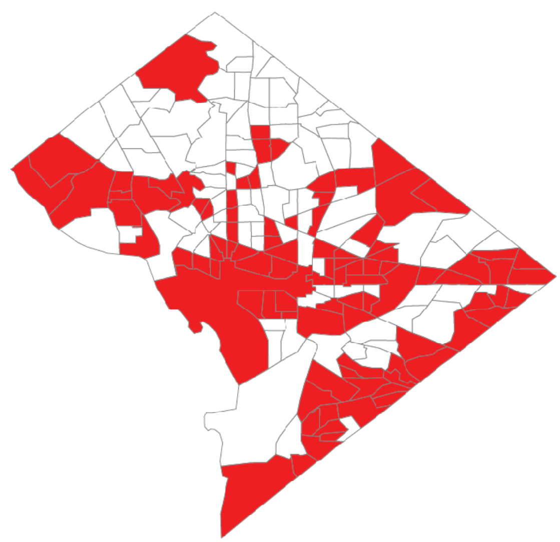
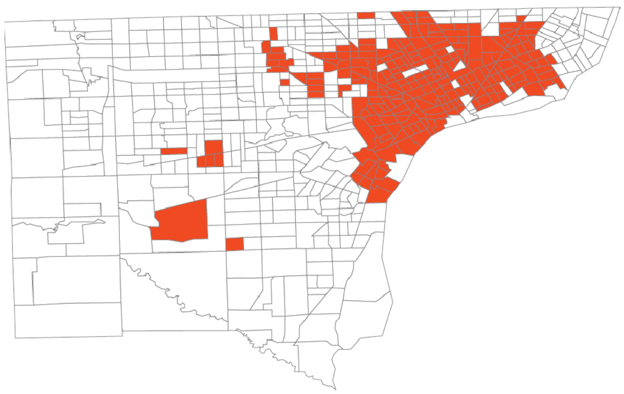
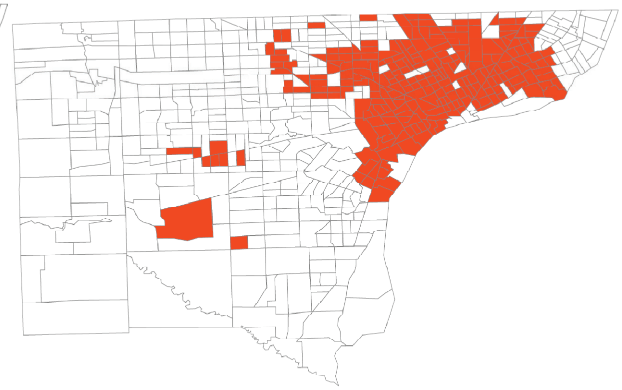


Fig 1. Washington, DC

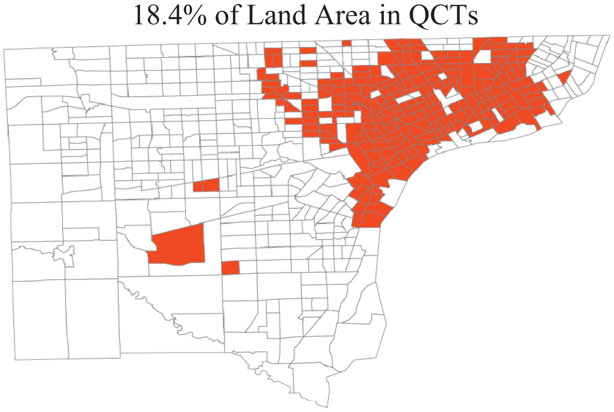
QCTs as of 2000 – 1990 Tract Boundaries
(237 QCTs out of 627 Tracts)
34.0% of Population in QCTs
17.4% of Land Area in QCTs



QCTs as of 2002 – 1990 Tract Boundaries
Formula Change (254 QCTs out of 627 Tracts)
36.7% of Population in QCTs
18.6% of Land Area in QCTs



QCTs as of 2003 – 2000 Tract Boundaries
Data Update (242 QCTs out of 620 Tracts)
34.7% of Population in QCTs
18.4% of Land Area in QCTs



QCTs as of 2007 – 2000 Tract Boundaries
Boundary Change (247 QCTs out of 620 Tracts)
35.6% of Population in QCTs
19.1% of Land Area in QCTs

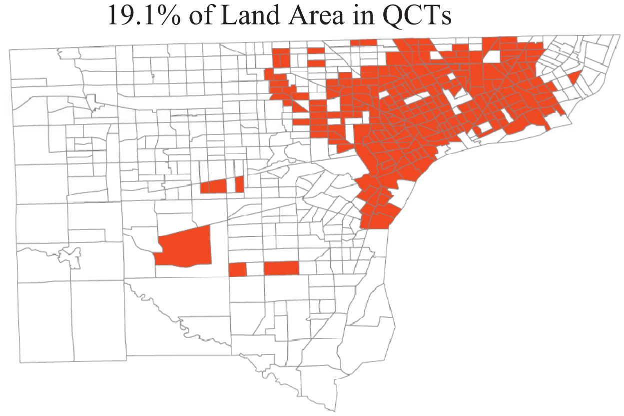


Fig 2. Wayne County (Detroit, Michigan)

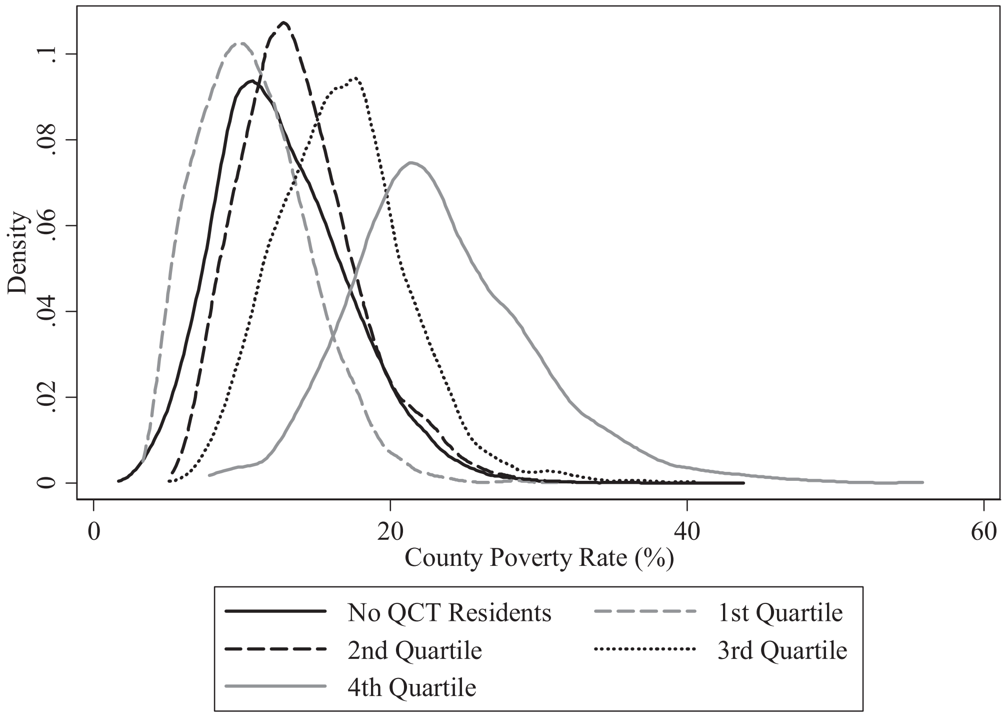


Fig 3. Distribution of County Poverty Rates by Population in QCTs

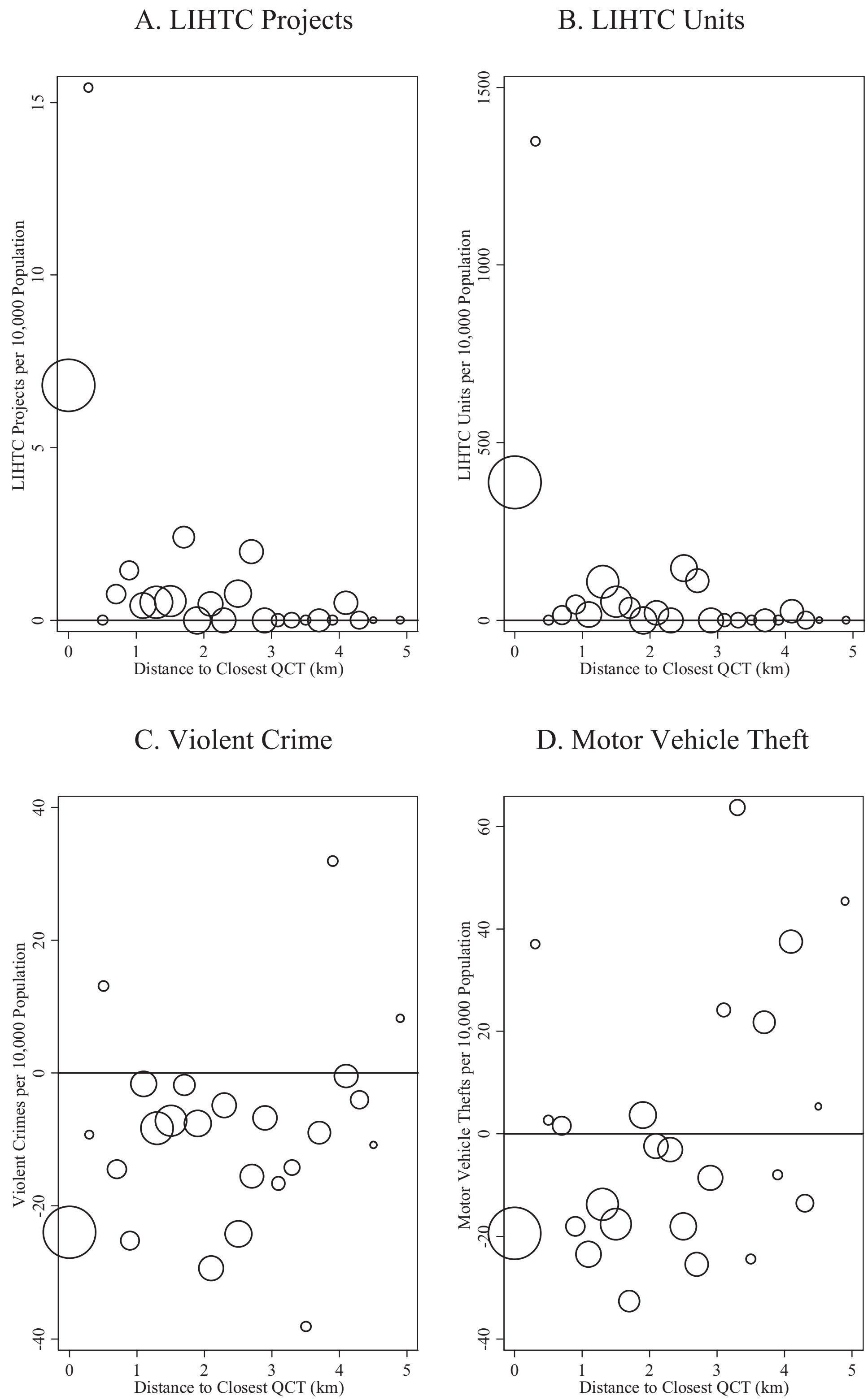


Fig 4. LIHTC Development and Changes in Crime Rates between 2001 and 2002 within 0.2km Bins from Nearest QCT, Seattle

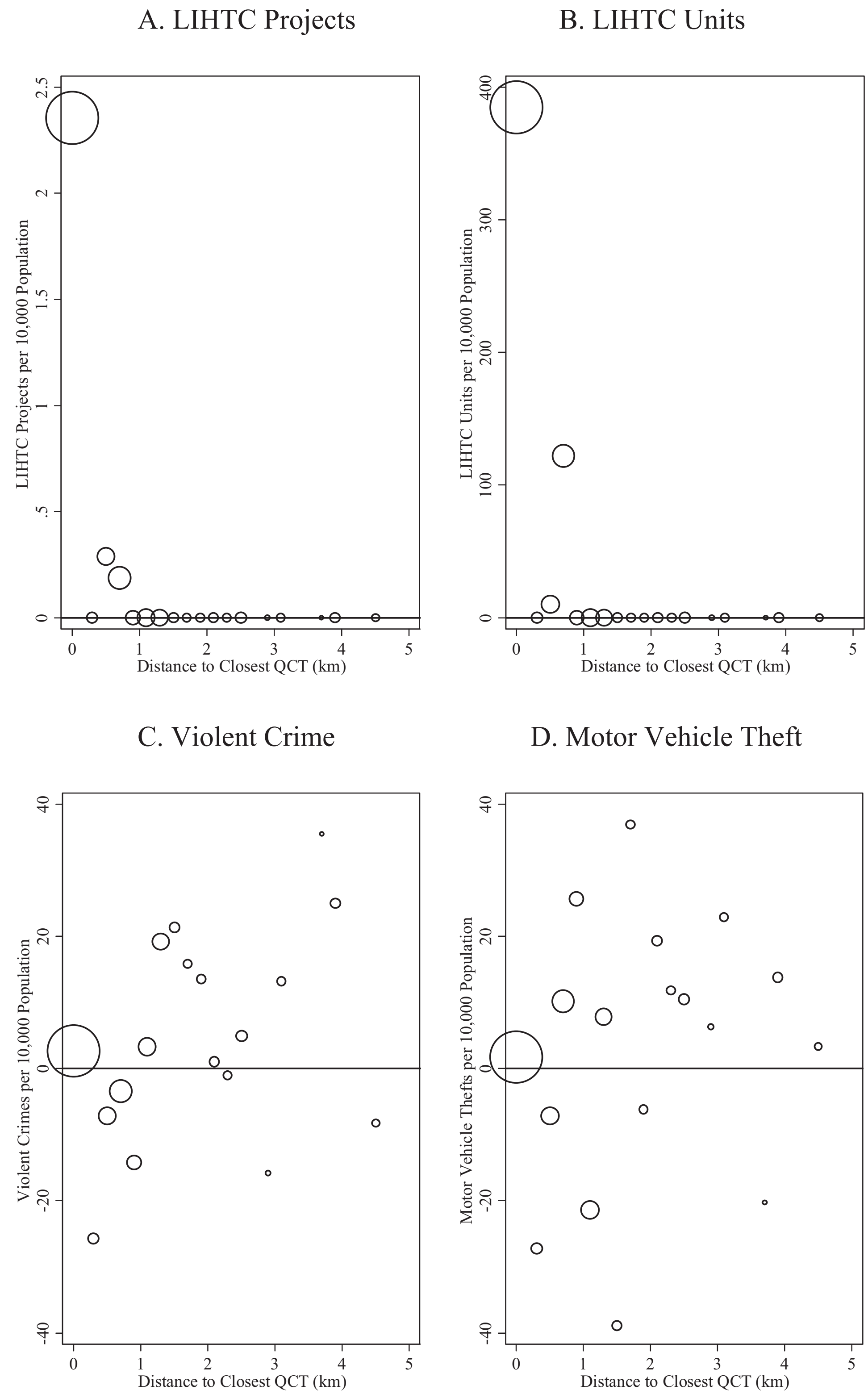


Fig 5. LIHTC Development and Changes in Crime Rates between 2006 and 2007 within 0.2km Bins from Nearest QCT, Washington, DC

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

	Mean	Standard Deviation	Minimum	Maximum
Housing Measures				
QCT Units per 10,000	4.22	15.57	0	511.99
LIHTC Units per 10,000	38.04	37.64	0	731.48
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 measures are 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)
	Murders	Rapes	Robberies	Assaults	Violent Crimes	Burglaries	MV Thefts	Larceny	Arson	Property Crimes
QCT Units Rate	0.00380**	0.00728**	0.0963**	0.0620*	0.169**	0.111*	0.209**	0.670**	0.00637*	0.997**
	[0.00116]	[0.00214]	[0.0226]	[0.0246]	[0.0454]	[0.0542]	[0.0604]	[0.115]	[0.00280]	[0.205]
Share Black	1.074**	0.0984	16.65**	27.98**	45.81**	47.04**	14.79**	75.75**	-0.227	137.4**
	[0.0755]	[0.249]	[1.198]	[3.392]	[4.190]	[5.741]	[3.204]	[15.07]	[0.282]	[21.41]
Share Age 15-24	-1.056**	6.525**	-10.17**	-31.41**	-36.12**	-43.38**	-37.95**	291.1**	-0.423	209.3**
	[0.143]	[1.001]	[2.517]	[6.841]	[8.702]	[13.38]	[6.178]	[50.25]	[0.751]	[63.28]
Poverty Rate	0.00614*	-0.00833	-0.0672*	0.751**	0.681**	0.476+	0.258*	-0.685	0.0217	0.0705
	[0.00250]	[0.0178]	[0.0336]	[0.138]	[0.167]	[0.252]	[0.111]	[0.677]	[0.0172]	[0.980]
Log Median HH Income	-0.143*	-0.626	-2.650**	-0.63	-4.048	-34.05**	0.667	-34.11+	-0.208	-67.70*
	[0.0569]	[0.528]	[0.858]	[3.486]	[4.318]	[6.415]	[3.019]	[18.70]	[0.493]	[27.00]
Log Population	0.0432**	0.416**	2.431**	3.359**	6.249**	11.13**	6.009**	35.96**	0.312**	53.41**
	[0.00718]	[0.0421]	[0.118]	[0.338]	[0.428]	[0.694]	[0.384]	[1.991]	[0.0560]	[2.896]
R-Squared	0.105	0.073	0.508	0.18	0.293	0.25	0.342	0.299	0.0354	0.327
Observations	22969	22969	22969	22969	22969	22969	22969	22969	22969	22969
F-Statistic	33.75	40.41	70.36	56.21	79.05	61.81	44.77	95.14	14.29	94.46

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)
	Murders	Rapes	Robberies	Assaults	Violent Crimes	Burglaries	MV Thefts	Larceny	Arson	Property Crimes
QCT Units Rate	0.00072	0.00189	0.0078	-0.0221	-0.0117	0.0207	-0.0317+	-0.132	-0.00503+	-0.148
	[0.00079]	[0.00221]	[0.00526]	[0.0208]	[0.0228]	[0.0300]	[0.0188]	[0.0820]	[0.00287]	[0.109]
Share Black	1.640	5.358	22.57**	55.42*	84.98**	87.25	-8.53	-214.0+	-1.601	-136.9
	[1.110]	[3.470]	[6.130]	[22.13]	[25.15]	[74.79]	[23.10]	[110.3]	[4.272]	[167.6]
Share Age 15-24	0.736	7.226	2.023	-28.87	-18.88	16.32	74.97	443.9	12.04	547.2
	[1.099]	[4.626]	[2.890]	[22.71]	[22.29]	[93.96]	[66.34]	[308.2]	[19.95]	[482.3]
Poverty Rate	0.00967+	0.0152	-0.0151	-0.12	-0.11	0.148	0.112	1.321+	0.0519	1.633
	[0.00565]	[0.0167]	[0.0168]	[0.0890]	[0.0963]	[0.218]	[0.129]	[0.746]	[0.0355]	[1.076]
Log Median HH Income	0.124	0.217	0.615	1.263	2.219	-2.752	-0.877	4.273	0.601	1.246
	[0.198]	[0.629]	[0.585]	[3.000]	[3.326]	[4.922]	[2.103]	[13.97]	[0.589]	[17.70]
Log Population	-0.0893	-0.104	0.44	-8.155+	-7.908+	-26.24**	-0.337	-60.69**	-0.891	-88.16**
	[0.197]	[0.429]	[0.532]	[4.357]	[4.520]	[9.376]	[3.489]	[15.59]	[0.555]	[25.06]
R-Squared	0.307	0.582	0.932	0.801	0.854	0.825	0.887	0.884	0.435	0.889
Observations	22969	22969	22969	22969	22969	22969	22969	22969	22969	22969
F-Statistic	1.409	3.697	9.083	3.044	3.393	8.8	9.704	16.88	2.784	15.84

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
Low-income housing and Qualified Census Tract coverage (first stage).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	QCT Units				LIHTC Units	Non-QCT Units	Falsified QCTs
Pop. in QCTs	8.997**	13.55**	13.08**	12.77**	2.383	-11.17**	2.973**
	[1.334]	[2.049]	[2.000]	[2.016]	[3.076]	[3.089]	[1.101]
Pop. Entering QCTs		-10.43**	-10.43**	-9.833**	-0.798	9.627**	-1.163
		[1.815]	[1.815]	[1.790]	[2.459]	[2.330]	[1.403]
Pop. Exiting QCTs		-0.857	-0.868	-1.033	4.135**	4.992**	-0.786
		[0.761]	[0.761]	[0.780]	[1.272]	[1.437]	[0.499]
Pop. in QCTs x No QCT Preference			6.877				
			[7.140]				
Share Black	-12.96	-11.71	-11.1	-25.41	-89.53+	-77.82*	-8.069
	[23.34]	[23.33]	[23.37]	[23.71]	[47.54]	[38.87]	[6.658]
Share Age 15-24	-55.79+	-49.05+	-48.59+	-52.72+	-139.4**	-90.31**	0.188
	[28.68]	[28.49]	[28.50]	[30.46]	[34.73]	[25.70]	[7.081]
Poverty Rate	0.275**	0.246**	0.246**	0.201**	0.548**	0.302**	-0.0262
	[0.0719]	[0.0711]	[0.0709]	[0.0679]	[0.103]	[0.0814]	[0.0442]
Log Median HH Income	2.666	1.327	1.369	1.374	-1.583	-2.91	-1.507
	[2.695]	[2.670]	[2.673]	[2.787]	[4.027]	[3.399]	[0.999]
Log Population	-1.245	0.378	0.396	1.11	9.305+	8.927*	0.654
	[2.558]	[2.552]	[2.553]	[2.700]	[5.363]	[4.363]	[0.697]
R-Squared	0.857	0.859	0.859	0.848	0.938	0.933	0.319
Observations	22,969	22,969	22969	21,588	22,969	22,969	22969
F-Statistic	22.46	19.94	18.72	18.59	84.22	75.67	3.83

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]	[2.91]	[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	-1.200	0.535	3.226	-0.0301	1.010
	[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
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

Low-income housing and violent crimes (IV).

	(1)	(2)	(3)	(4)	(5)	(6)
	Murders	Rapes	Robberies	Assaults	Violent Crimes	Violent Crimes
QCT Units Rate	0.00794	0.00499	-0.0808**	-0.377+	-0.444*	-0.437+
	[0.00680]	[0.0166]	[0.0313]	[0.205]	[0.222]	[0.249]
Pop. Entering QCTs	0.0321	-0.104	0.111	1.866	1.904	2.094
	[0.0852]	[0.174]	[0.288]	[1.361]	[1.486]	[1.552]
Pop. Exiting QCTs	0.035	0.199	-0.317	-1.8	-1.882	-2.056
	[0.192]	[0.288]	[0.411]	[1.617]	[1.876]	[1.910]
Share Black	1.765+	5.403+	21.07**	49.54*	77.78**	86.95**
	[1.052]	[3.246]	[5.978]	[21.51]	[24.56]	[25.64]
Share Age 15-24	1.171	7.451+	-3.496	-51.44*	-46.32+	-46.86+
	[1.129]	[4.398]	[3.985]	[25.10]	[25.87]	[28.04]
Poverty Rate	0.0079	0.0148	0.0083	-0.0244	0.00663	-0.0217
	[0.00539]	[0.0164]	[0.0171]	[0.105]	[0.114]	[0.116]
Log Median HH Income	0.112	0.198	0.834	2.333	3.477	4.56
	[0.185]	[0.589]	[0.577]	[2.980]	[3.316]	[3.425]
Log Population	-0.0718	-0.086	0.185	-9.298*	-9.271*	-9.004+
	[0.179]	[0.408]	[0.504]	[4.202]	[4.387]	[4.674]
Observations	22,962	22,962	22,962	22,962	22,962	21,585
F-Statistic	1.436	3.751	8.865	2.934	3.266	3.466

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

Low-income housing and property crimes (IV).

	(1)	(2)	(3)	(4)	(5)	(6)
	Burglaries	MV Thefts	Arson	Larceny	Property Crimes	Property Crimes
QCT Units Rate	0.0696	0.137+	0.0194	0.197	0.423	0.774
	[0.230]	[0.0765]	[0.0188]	[0.493]	[0.692]	[0.776]
Pop. Entering QCTs	1.255	-0.584	-0.261	-2.842	-2.432	-5.813
	[2.145]	[0.674]	[0.196]	[3.870]	[5.599]	[5.723]
Pop. Exiting QCTs	0.283	-1.484	0.14	-7.742	-8.803	-10.64
	[2.847]	[1.160]	[0.492]	[5.689]	[7.595]	[8.033]
Share Black	88.17	-5.724	-1.206	-208.7*	-127.4	-70.17
	[69.96]	[22.61]	[4.089]	[103.8]	[158.0]	[167.0]
Share Age 15-24	18.91	85.62	13.64	465.4	583.6	516.8
	[89.36]	[62.63]	[18.81]	[291.5]	[455.5]	[493.5]
Poverty Rate	0.139	0.0589	0.045	1.196+	1.439	1.503
	[0.211]	[0.120]	[0.0324]	[0.693]	[1.000]	[1.112]
Log Median HH Income	-2.683	-1.381	0.509	2.964	-0.592	9.428
	[4.641]	[2.036]	[0.557]	[13.03]	[16.58]	[17.47]
Log Population	-26.21**	0.169	-0.801	-59.59**	-86.42**	-87.06**
	[8.767]	[3.356]	[0.532]	[14.68]	[23.53]	[25.35]
Observations	22,962	22,962	22,962	22,962	22,962	21,585
F-Statistic	8.749	10.35	2.584	16.89	15.86	13.44

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

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	MV Thefts	Arson	Larceny	Property Crimes
QCT Units Rate	0.00845	0.0073	-0.0889**	-0.376+	-0.450*	0.0839	0.141+	0.0129	0.194	0.432
	[0.00718]	[0.0169]	[0.0311]	[0.204]	[0.220]	[0.232]	[0.0759]	[0.0186]	[0.486]	[0.688]
Pop. Entering QCTs	0.0462	-0.0287	0.0429	1.686	1.747	0.858	-0.264	-0.205	-0.749	-0.36
	[0.0894]	[0.191]	[0.285]	[1.394]	[1.513]	[2.186]	[0.697]	[0.202]	[3.871]	[5.641]
Pop. Exiting QCTs	0.0223	0.228	-0.417	-2.797+	-2.963	-0.775	-1.106	0.0937	-6.53	-8.317
	[0.199]	[0.294]	[0.420]	[1.673]	[1.939]	[2.907]	[1.167]	[0.498]	[5.621]	[7.419]
Share Black	1.682	8.078*	18.25**	43.91+	71.92**	81.89	2.182	-0.962	-116.2	-33.11
	[1.052]	[3.281]	[5.767]	[23.23]	[26.30]	[69.59]	[21.47]	[4.082]	[104.6]	[157.9]
Share Age 15-24	1.683	7.583+	-1.037	-30.45	-22.22	64.14	96.33	14.86	529.4+	704.7
	[1.100]	[3.957]	[3.910]	[23.01]	[24.19]	[92.92]	[65.54]	[19.85]	[306.3]	[478.3]
Poverty Rate	0.00854+	0.0137	0.0152	-0.0485	-0.0111	0.126	0.0636	0.0529	1.049	1.291
	[0.00500]	[0.0172]	[0.0175]	[0.101]	[0.109]	[0.204]	[0.121]	[0.0322]	[0.687]	[0.988]
Log Median HH Income	0.133	-0.0462	0.901	2.956	3.944	-3.303	-2.232	0.391	-2.935	-8.079
	[0.182]	[0.591]	[0.586]	[2.988]	[3.326]	[4.457]	[2.047]	[0.521]	[12.17]	[15.46]
Log Population	-0.24	0.146	-1.266+	-17.16**	-18.52**	-46.77**	-2.149	-0.585	-67.35**	-116.9**
	[0.210]	[0.486]	[0.753]	[5.344]	[5.555]	[9.919]	[4.196]	[0.623]	[17.86]	[28.48]
Observations	22,962	22,962	22,962	22,962	22,962	22,962	22,962	22,962	22,962	22,962
F-Statistic	1069.5	77674.1	667.9	481.6	246	654.7	375.3	422	192.2	709.2

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 A1
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	0.0209	-0.0320+	-0.133	-0.00507+	-0.149	0.000726	0.00189	0.00783	-0.0217	-0.0113
	[0.0301]	[0.0188]	[0.0821]	[0.00287]	[0.109]	[0.000793]	[0.00222]	[0.00525]	[0.0208]	[0.0228]
Pop. Entering QCTs	1.175	-0.862	-3.388	-0.302	-3.376	0.0202	-0.11	0.257	2.451+	2.618
	[2.324]	[0.702]	[4.340]	[0.208]	[6.205]	[0.0920]	[0.184]	[0.296]	[1.472]	[1.609]
Pop. Exiting QCTs	0.184	-1.83	-8.42	0.0898	-9.977	0.0202	0.193	-0.135	-1.072	-0.994
	[2.991]	[1.175]	[5.869]	[0.524]	[7.818]	[0.206]	[0.307]	[0.432]	[1.616]	[1.898]
Share Black	87.34	-8.606	-214.3+	-1.624	-137.2	1.641	5.35	22.58**	55.60*	85.18**
	[74.79]	[23.10]	[110.3]	[4.271]	[167.5]	[1.110]	[3.470]	[6.131]	[22.13]	[25.16]
Share Age 15-24	15.93	75.28	445.1	12.14	548.5	0.729	7.261	1.939	-29.68	-19.75
	[93.93]	[66.35]	[308.1]	[19.94]	[482.2]	[1.100]	[4.624]	[2.884]	[22.65]	[22.22]
Poverty Rate	0.152	0.103	1.283+	0.0514	1.589	0.00979+	0.0156	-0.015	-0.118	-0.107
	[0.220]	[0.130]	[0.752]	[0.0356]	[1.084]	[0.00568]	[0.0168]	[0.0169]	[0.0889]	[0.0961]
Log Median HH Income	-2.582	-1.029	3.653	0.56	0.602	0.127	0.205	0.649	1.593	2.574
	[4.947]	[2.106]	[14.03]	[0.591]	[17.79]	[0.198]	[0.631]	[0.589]	[2.993]	[3.324]
Log Population	-26.34**	-0.276	-60.46**	-0.866	-87.94**	-0.0909	-0.0941	0.418	-8.361+	-8.128+
	[9.377]	[3.494]	[15.59]	[0.555]	[25.07]	[0.196]	[0.431]	[0.531]	[4.350]	[4.512]
R-Squared	0.825	0.888	0.884	0.435	0.889	0.307	0.582	0.932	0.801	0.854
Observations	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969
F-Statistic	7.637	9.023	14.94	2.507	13.96	1.224	3.287	7.879	2.739	3.004

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 A2

Qualified Census Tract coverage and violent crimes: Excluding counties with DDAs and no explicit QCT preference (reduced form).

	(1)	(2)	(3)	(4)	(5)
	Murders	Rapes	Robberies	Assaults	Violent Crimes
Pop. in QCTs	0.13	0.124	-1.017*	-4.819	-5.582+
	[0.102]	[0.237]	[0.442]	[3.078]	[3.313]
Pop. Entering QCTs	-0.043	-0.171	0.833*	5.773*	6.393*
	[0.122]	[0.244]	[0.371]	[2.841]	[3.078]
Pop. Exiting QCTs	0.04	0.0117	-0.377	-1.279	-1.604
	[0.218]	[0.277]	[0.447]	[1.640]	[1.951]
Share Black	1.825	5.928+	25.36**	64.95**	98.06**
	[1.178]	[3.580]	[6.091]	[22.66]	[25.55]
Share Age 15-24	0.734	6.605	-1.546	-29.61	-23.81
	[1.166]	[4.894]	[2.945]	[23.77]	[23.34]
Poverty Rate	0.00973+	0.0183	-0.0111	-0.126	-0.109
	[0.00583]	[0.0181]	[0.0176]	[0.0960]	[0.103]
Log Median HH Income	0.109	0.489	0.84	2.521	3.959
	[0.209]	[0.660]	[0.605]	[3.085]	[3.433]
Log Population	-0.109	-0.016	0.113	-9.477*	-9.489*
	[0.211]	[0.461]	[0.517]	[4.694]	[4.827]
R-Squared	0.306	0.58	0.933	0.799	0.853
Observations	21,588	21,588	21,588	21,588	21,588
F-Statistic	1.335	3.386	7.466	2.886	3.213

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 A3

Qualified Census Tract coverage and property crimes: Excluding counties with DDAs and no explicit QCT preference (reduced form).

	(1)	(2)	(3)	(4)	(5)
	Burglaries	MV Thefts	Arson	Larceny	Property Crimes
Pop. in QCTs	2.996	1.833+	0.356	4.693	9.877
	[3.438]	[1.028]	[0.276]	[7.457]	[10.54]
Pop. Entering QCTs	-2.139	-2.302*	-0.623*	-8.355	-13.42
	[3.486]	[1.032]	[0.282]	[7.604]	[10.66]
Pop. Exiting QCTs	-0.133	-2.402*	0.194	-9.098	-11.44
	[3.057]	[1.029]	[0.557]	[6.045]	[8.360]
Share Black	88.34	1.16	-1.252	-178.1	-89.83
	[79.19]	[23.30]	[4.578]	[115.8]	[176.1]
Share Age 15-24	-0.337	69.19	13.41	393.8	476.1
	[101.6]	[71.77]	[21.50]	[333.2]	[522.5]
Poverty Rate	0.162	0.0908	0.0502	1.356	1.659
	[0.242]	[0.146]	[0.0396]	[0.834]	[1.207]
Log Median HH Income	-1.423	-0.893	0.719	12.09	10.49
	[5.115]	[2.195]	[0.634]	[14.59]	[18.57]
Log Population	-25.26*	1.09	-0.811	-61.22**	-86.20**
	[10.24]	[3.847]	[0.597]	[16.78]	[27.24]
R-Squared	0.824	0.889	0.432	0.883	0.887
Observations	21,588	21,588	21,588	21,588	21,588
F-Statistic	7.765	8.456	2.127	12.23	11.85

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 A4

Low-income housing and Qualified Census Tract coverage: Area-based measures (first stage).

	(1)	(2)	(3)	(4)	(5)	(6)
	QCT Units				LIHTC Units	Non-QCT Units
Area in QCTs	6.291**	10.07**	9.837**	9.630**	-0.563	-10.63*
	[1.836]	[2.818]	[2.917]	[2.993]	[4.592]	[4.606]
Area Entering QCTs		-8.294**	-8.232**	-7.851**	1.613	9.908**
		[2.318]	[2.321]	[2.418]	[3.588]	[3.629]
Area Exiting QCTs		-0.0467	-0.043	-0.153	2.668*	2.715*
		[0.579]	[0.577]	[0.593]	[1.306]	[1.340]
Area in QCTs x No QCT Preference			2.126			
			[5.920]			
Share Black	-13.94	-12.61	-12.21	-26.63	-90.79+	-78.18*
	[23.28]	[23.19]	[23.33]	[23.65]	[47.27]	[38.78]
Share Age 15-24	-59.24*	-55.73*	-55.78*	-58.41*	-141.7**	-85.99**
	[28.26]	[27.54]	[27.49]	[29.28]	[34.31]	[25.67]
Poverty Rate	0.278**	0.262**	0.263**	0.216**	0.549**	0.287**
	[0.0724]	[0.0726]	[0.0726]	[0.0696]	[0.104]	[0.0818]
Log Median HH Income	2.751	1.808	1.837	1.767	-1.376	-3.184
	[2.664]	[2.717]	[2.727]	[2.843]	[4.051]	[3.403]
Log Population	-2.004	-0.909	-0.924	-0.0396	8.623	9.532*
	[2.682]	[2.817]	[2.825]	[3.009]	-0.563	[4.278]
R-Squared	0.856	0.857	0.857	0.847	0.938	0.933
Observations	22969	22969	22969	21588	22969	22969
F-Statistic	22.59	19.76	18.54	18.42	84.42	75.32

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 A6.1
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 A6.2

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%.