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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 in the poorest neighborhoods brings with it significant reductions in violent crime that are measurable at the county level. There are no detectable effects on property crime.

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. This 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 development, 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. Consistent with this result, we provide further suggestive evidence using tract-level data for two cities that the reductions in violent crime associated with housing development under 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-

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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 may not only provide incentives for low-income residents to stay, but may also attract 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 affordable rental housing development program, the LIHTC program, has highlighted these potential offsetting effects. The LIHTC program, 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 the LIHTC program is not contributing to the concentration of poverty, and that, in fact, it might be doing the opposite. However, they contend that tax incentives that steer projects toward high poverty neighborhoods limit the extent to which affordable housing developments find their way to lower poverty communities, and in turn hinder the ability of 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; McNulty and Holloway, 2000). These studies, which typically focus on public housing projects, point out that the demographic groups more often involved in crime are disproportionately found in low-income housing. Hence, building new affordable housing could affect local crime by attracting individuals from other neighborhoods who might be more prone to criminal activity. The concentration of poverty itself could further exacerbate crime problems in neighborhoods (Glaeser et al., 1996; Bjerk, 2010).

In contrast, research on social disorganization and crime suggest that improvements in the housing stock in low-income areas could reduce illicit activity. Not only might new housing attract less criminal residents, but it also might dilapidated structures and vacant lots, which foster criminal behavior (Wilson and Kelling, 1982).

A related literature examines how changes in neighborhood conditions affect individual behavior. Multiple studies of the Moving to Opportunity 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). A smaller number of studies have considered how initiatives that target particular neighborhoods or regions for capital or infrastructure investment, as opposed to programs that encourage people to move to areas already more economically vibrant, affect crime. For example, Cook and Macdonald (2011) 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.[1]

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.

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). State housing agencies have discretion over which projects receive tax credits,

[1] Consistent with Cook and Macdonald (2011) 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.

but federal law requires states to file Qualified Allocation Plans (QAPs) that document any preferences or set-asides within their tax credit competitions.

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. 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.[2]

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. Prior to 2002, a census tract qualified as a QCT if 50% of its households had incomes below 60% of the AMGI unless the total population of designated QCTs within a metropolitan area exceeds 20% of that metropolitan area's population.[3]

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,[4] developers have an explicit incentive to locate in a QCT even within DDAs. Gustafson and Walker (2002) note that nearly all state QAPs 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 a tax credit.

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 qualifies 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 increased the number of designated tracts from 7700 in 2001 to over 9900 in 2002 (Hollar and Usowski, 2007). The share of the U.S. population living in QCTs jumped from under 10% to over 13%.[5]

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. About 5% of all tracts changed status as a result of the update, with roughly half switching from unqualified to qualified and half from qualified to unqualified. Changes in QCT status arose largely because of changes in poverty and income levels within tracts, but also partly because of changes in the geographic boundaries of tracts and their corresponding metropolitan areas.

In intercensal years, QCT designations can change to reflect metropolitan area redefinitions. Changes in the boundaries of metropolitan areas affect 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.

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 subsidized by the LIHTC program 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.[6]

The HUD data on developments include all projects receiving tax credits through the LIHTC program and, for most developments, have information on the exact location of the project, the year the project was placed in service, the 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.[7]

Of the 31,087 projects placed in service between 1987 and 2007, we have usable data on 29,870.[8] These projects represent approximately 1.8 million units. About 55% of the projects were new construction, while most of the remainder were rehabilitations.[9] We define 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 16,000 tracts, and just over one fourth of all projects and units are located in QCTs.

Aggregating 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 in QCTs, and the share of the county's population 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 over time.

[2] 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.

[3] 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.

[4] 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.

[5] These population figures are based on the 1990 Decennial Census. Prior to 2003, HUD used 1990-vintage geographic boundaries.

[6] 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.

[7] We also observe the year that funds were allocated to each project; for about one third of the projects, the fund allocation and placed in service years are the same, while for nearly all of the remaining two thirds, the year placed in service is either 1 or 2 years after the year the funds were allocated to the project.

[8] Of the 31,087 projects in the U.S. (excluding Puerto Rico, Guam, and the U.S. Virgin Islands), there were 254 projects that had no year placed in service information, and an additional 330 projects were missing information on number of units. Of the 30,503 projects remaining, 2394 projects had no tract geography information. However, using street addresses and project names, we were able to assign tract codes to 1761 of the projects missing geography data.

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

Table 1
Descriptive statistics.

	Mean	Standard deviation	Minimum	Maximum
Housing measures				
QCT units/10,000 county residents	4.22	15.57	0	511.99
LIHTC units/10,000 county residents	38.04	37.64	0	731.48
Pop. in QCTs/10,000 county residents	0.084	0.17	0	1
Pop. entering QCTs/10,000 county residents	0.012	0.07	0	1
Pop. exiting QCTs/10,000 county residents	0.006	0.05	0	1
Crime measures				
Total crimes/10,000 county residents	261.56	166.92	0	3818.18
Violent crimes/10,000 county residents	27.25	25.67	0	809.92
Murders/10,000 county residents	0.35	0.69	0	24.10
Rapes/10,000 county residents	2.45	2.44	0	73.59
Robberies/10,000 county residents	4.10	7.00	0	140.02
Assault/10,000 county residents	20.36	20.45	0	808.93
Property crimes/10,000 county residents	234.31	148.92	0	3636.36
Burglary/10,000 county residents	55.94	37.93	0	909.09
Larceny/10,000 county residents	159.82	106.29	0	2363.64
MV theft/10,000 county residents	16.86	17.90	0	343.81
Arson/10,000 county residents	1.69	2.44	0	181.82
Demographic measures				
County poverty rate	0.141	0.057	.017	0.559
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			

Note: Data are averages over the years 2000–2007.

Table 1 provides descriptive statistics for the sample that forms the basis for our empirical analysis. The average county has about 38 LIHTC units per ten thousand residents, and on average, four LIHTC units per ten thousand residents are located in QCTs.[10] As we describe below, we use the share of the county's population living in QCTs as an instrument for low-income housing development. The average share of a county's population in QCTs over the sample period was 8.4%. 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.

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 (UCR), but the UCRC 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. The county-level data provide for a more direct mapping to HUD and Census data than the UCR, which contains data at the police jurisdiction level.[11]

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 violent crimes and 234 property crimes per ten thousand county residents in our sample. The most common violent crime is aggravated assault; there are an average of 20 aggravated assaults per ten thousand county residents in our sample. Other violent crimes, including murders, rapes, and robberies, are much less common, each with fewer than five per ten thousand county residents on average.[12] The most common property crime is larceny, with an average of 160 offenses per ten thousand county residents. Burglaries, motor vehicle theft, and arson, the other main types of property crime, occur less frequently, with 56, 17, and two reported offenses per ten thousand county residents on average, respectively.

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 present evidence that within counties, QCTs tend to attract development away from non-QCTs as opposed to increase the total amount of low-income housing. This suggests that, within counties, even tracts that never qualified do not represent suitable controls for tracts with QCT status, as patterns of development in both QCTs and non-QCTs are affected by the federal rule changes we exploit.

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, 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

[10] 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.

[11] 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. The ICPSR imputes the annual number of offenses known to police in each county to construct the UCRC. The UCRC contains a "coverage indicator" variable for each observation, which ranges from 0 to 100 and 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.

[12] 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.

residents from elsewhere in the county, it may increase crime in affected areas but decrease it in neighboring communities. From a policy standpoint, the aggregate crime rate, rather than the geographic distribution of criminal activity, 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 (see, for example, Rosenthal and Ross, 2010), but our identification strategy requires a relatively large sample. The UCRC strikes a reasonable balance between geographic detail and scope.[13]

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 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.[14] 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.[15] 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 more importantly, a county-level analysis obscures the precise geographic sources of changes in crime in response to low-income housing development. An observed change in crime at the county level could be driven by changes in tracts that receive new investment, changes in tracts that do not receive investment but experience spillovers from those that do, or both. 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 in the immediate vicinity of QCTs that are not offset by increases in surrounding neighborhoods. This highlights the localized nature of the crime reduction effects we find at the county level and points to the potential for residential investment spurred by the LIHTC program to improve struggling neighborhoods without harming nearby areas. 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 low-income housing development 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.

As an instrument for low-income housing development, we construct a county-level measure that captures the incentives developers have to build or rehabilitate affordable housing in certain 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.[16] 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

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

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 $\mathbf{X}$ 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.[17] In this and all regressions that follow, we adjust the standard errors for heteroskedasticity and clustering at the county level.[18]

In some specifications, we also control for "churn" in QCT status by including in $\mathbf{X}$ the fraction of the county population living in tracts that gained QCT status as well as the fraction of the population living in tracts 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.

To illustrate, consider the changes in QCT coverage in Washington, DC and Wayne County, Michigan (which includes Detroit), depicted in Figs. 1 and 2. The fraction of residents living in QCTs grew by a similar amount in each county between 2000 and 2007, but these comparable increases mask considerable differences in the degree of churn in QCT status. Counties such as Washington, DC that experienced substantial changes over time in the spatial distribution of households and income, and thus in QCTs, likely had different patterns of low-income housing development (as well as crime) than counties that more closely resemble Wayne County in terms of its lack of pronounced shifts in the locations of more and less affluent neighborhoods. Controlling for the fraction of

[13] Some of the statistical problems with the UCRC, which Maltz (1999) discuss in detail, are not present in the police jurisdiction-level UCR. However, the aggregation from census tract to county is more straightforward than aggregation from census tract to police jurisdiction.

[14] Sampson et al. (1997) highlight the strong association between crime and neighborhood disadvantage.

[15] 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% reduction in crime in a tract that only contributes 10% to the aggregate crime rate will only reduce county-level crime by 2.5%.

[16] 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). However, our results are generally robust to using an area-based measure instead of a population-based one.

[17] 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.

[18] Clustering at the MSA level (with clusters for rural areas defined as the non-MSA balance of each state) yields standard errors that are nearly identical to those obtained by clustering at the county level.

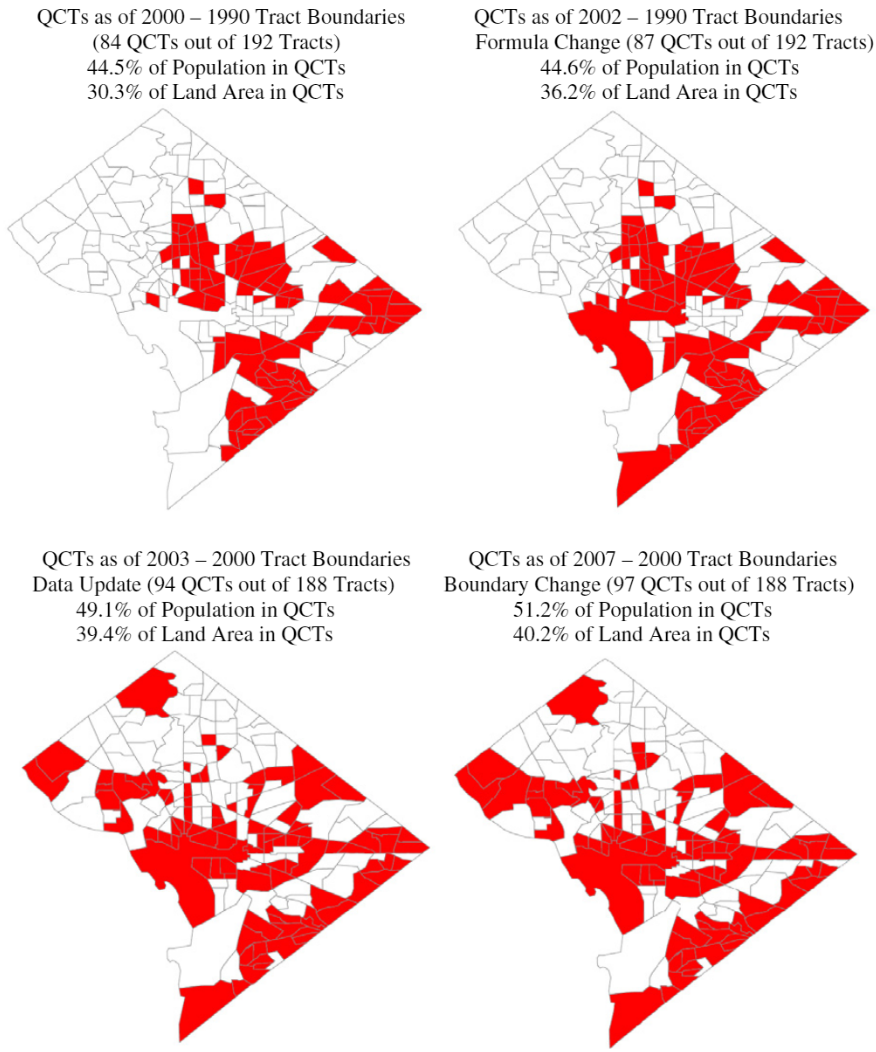

Fig. 1. Qualified census tracts in Washington, DC.

the QCT population that is "new" allows us to differentiate between places like Washington, DC and Detroit.

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:

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

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 the likelihood of receiving investment in affordable housing. 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 should only affect crime rates through its effects on changes in where low-income housing development occurs. The first stage and reduced form regressions, then, are

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

and

$$CrimeRate_{it} = \gamma QCT_{it} + \mathbf{X}_{it}\boldsymbol{\beta} + \mu_i + \eta_t + \upsilon_{it} \tag{4}$$

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 coverage 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 eligible for a larger tax credit. This mechanical relationship, however, should

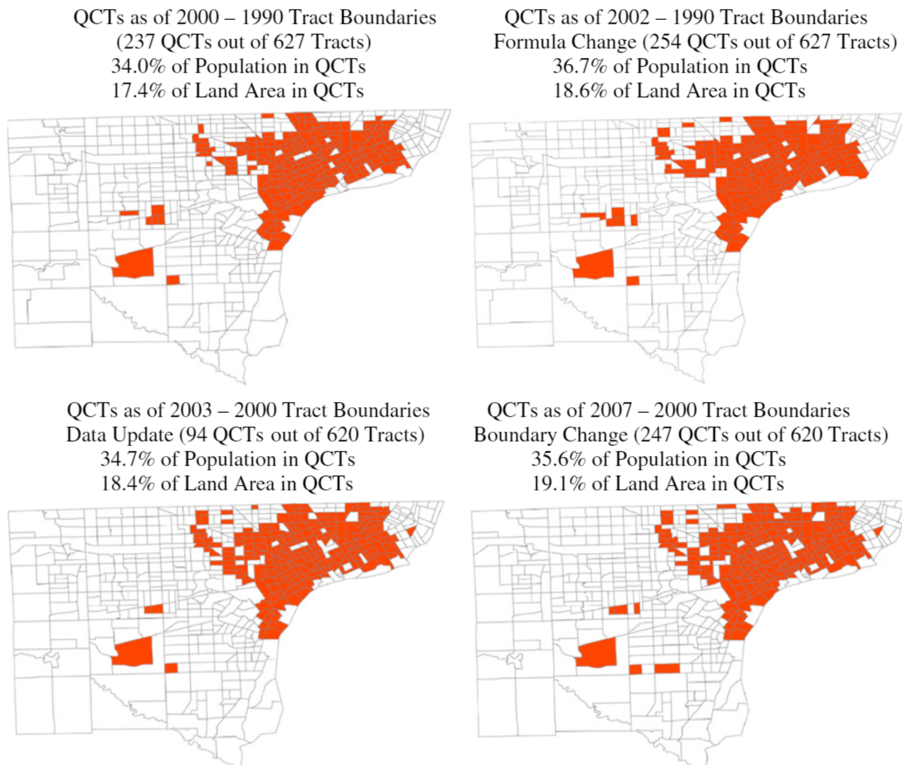

Fig. 2. Qualified census tracts in Wayne County, Michigan.

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, if some LIHTC developments would not have occurred in the absence of the program, or if LIHTC developments 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.[19]

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. However, we would expect different effects of neighborhood development on different types of crime. This is especially true if the likelihood of not only committing a crime, but also reporting one is correlated with neighborhood conditions. In particular, if community investment increases the propensity of residents to report crime to the police, our estimate of the effect of low-income housing development on crime, as measured in the UCRC, will 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 Eq. (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 ten thousand county residents 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

[19] 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).

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable									
	Murders	Rapes	Robberies	Assaults	Violent crimes	Burglaries	MV thefts	Larceny	Arson	Property crimes
QCT Units/10,000 county residents	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	1.07**	0.0984	16.6**	30.0**	45.8**	47.0**	14.8**	75.8**	−0.227	137**
	[0.0755]	[0.249]	[1.20]	[3.39]	[4.190]	[5.741]	[3.204]	[15.07]	[0.282]	[21.4]
Share age 15–24	−1.06**	6.52**	−10.2**	−31.4**	−36.1**	−43.4**	−38.0**	291**	−0.423	209**
	[0.143]	[1.00]	[2.52]	[6.84]	[8.70]	[13.4]	[6.18]	[50.2]	[0.751]	[63.3]
Poverty rate	0.614*	−0.833	−6.72*	7.51**	68.1**	47.6+	25.8*	−68.5	2.17	7.05
	[0.250]	[1.78]	[3.36]	[13.8]	[16.7]	[25.2]	[11.1]	[67.7]	[1.72]	[98.0]
Log median HH income	−0.143*	−0.626	−2.65**	−0.63	−4.05	−34.0**	0.667	−34.1+	−0.208	−67.70*
	[0.0569]	[0.528]	[0.858]	[3.49]	[4.32]	[6.42]	[3.02]	[18.70]	[0.493]	[27.00]
Log population	0.0432**	0.416**	2.43**	3.36**	6.25**	11.1**	6.01**	36.0**	0.312**	53.4**
	[0.00718]	[0.0421]	[0.118]	[0.338]	[0.428]	[0.694]	[0.384]	[1.991]	[0.0560]	[2.90]
R-squared	0.105	0.073	0.508	0.18	0.293	0.25	0.342	0.299	0.0354	0.327
Observations	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969

Notes: Dependent variables scaled by 10,000 county residents. All specifications include 7 year dummies. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets.
+ Significant at 10%.
* Significant at 5%.
** Significant at 1%.

both low-income housing and criminal activity. We would expect such omitted variables to bias the estimated coefficients on low-income housing development upward.

Indeed, once we include county fixed effects and estimate Eq. (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.[20] 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 coverage that is driven by the timing of changes in the formulas, data, and boundaries used by HUD, not variation in QCT coverage arising from continuous changes in county characteristics.

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%.[21] Notably, as indicated by the first stage *F*-statistics reported at the bottom of columns (1) and (2) of Table 4, our instrument appears to be highly relevant.[22]

[20] Controlling for churn in QCT coverage affects the estimates little.

[21] In results not shown, we find no evidence that the estimated effect of QCT coverage on the location of new development is driven only by states with QAPs that explicitly favor developments in QCTs. Further, limiting the sample to counties that are either not DDAs or that are located in states whose QAP gives preference to developments in QCTs does not affect the results substantively.

[22] Staiger and Stock (1997) suggest that when the *F*-statistic exceeds 10, as it does in both specifications, weak instrument bias is small. Though this rule of thumb assumes that the model errors are i.i.d., the Kleibergen-Paap test statistics (reported in Tables 8 and 9), which are robust to heteroskedasticity, also indicate that our instruments are not weak.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable									
	Murders	Rapes	Robberies	Assaults	Violent crimes	Burglaries	MV thefts	Larceny	Arson	Property crimes
QCT units/10,000 county residents	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	1.64	5.36	22.6**	55.4*	85.0**	87.2	−8.53	−214+	−1.60	−137
	[1.11]	[3.47]	[6.13]	[22.1]	[25.2]	[74.8]	[23.1]	[110]	[4.27]	[168]
Share age 15–24	0.736	7.23	2.02	−28.9	−18.9	16.3	75.0	443.9	12.0	547
	[1.10]	[4.63]	[2.89]	[22.7]	[22.3]	[94.0]	[66.3]	[308.2]	[20.0]	[482]
Poverty rate	0.967+	1.52	−1.51	−12.0	−11.0	14.8	11.2	132.1+	5.19	163
	[0.565]	[1.67]	[1.68]	[8.90]	[9.63]	[21.8]	[12.9]	[74.6]	[3.55]	[108]
Log median HH income	0.124	0.217	0.615	1.26	2.22	−2.75	−0.877	4.273	0.601	1.25
	[0.198]	[0.629]	[0.585]	[3.00]	[3.33]	[4.92]	[2.10]	[13.97]	[0.589]	[17.7]
Log population	−0.0893	−0.104	0.44	−8.16+	−7.91+	−26.2**	−0.337	−60.69**	−0.891	−88.2**
	[0.197]	[0.429]	[0.532]	[4.36]	[4.52]	[9.38]	[3.49]	[15.59]	[0.555]	[25.1]
R-squared	0.307	0.582	0.932	0.801	0.854	0.825	0.887	0.884	0.435	0.889
Observations	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969

Notes: Dependent variables scaled by 10,000 county residents. 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%.
* Significant at 5%.
** Significant at 1%.

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

In column (3) of Table 4, we estimate the impact of changes in the fraction of the population in a QCT on all low-income housing development in a county and find a positive relationship. However, the estimated coefficient is smaller than the standard error. Also, the magnitude of the estimated relationship is small, corresponding to an elasticity of approximately 0.5%. In column (4), we see that increases in the fraction of the county's QCT population are associated with reductions the number of low-income housing units in wealthier (non-QCT) areas. Though we cannot pin down the precise magnitude of the crowd-out effect in this county-level analysis, our results are consistent with 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 (5) of Table 4, in which we use these counterfactual measures of population and projects in QCTs, show that there is a positive mechanical relationship between the fraction of a county designated as QCT and the number of QCT housing units. 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 (5) 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. 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.[23] 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.

Meanwhile, we find no substantive relationship between changes in the share of people living in a QCT and changes in prop-

[23] Cook and MacDonald (2011) also find that robberies and assaults fell more so than other crimes in Business Improvement Districts in Los Angeles.

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

	(1)	(2)	(3)	(4)	(5)
	Dependent variable				
	QCT units		LIHTC units	Non-QCT units	Falsified QCTs
Pop. in QCTs/10,000 county residents	9.00**	13.6**	2.38	−11.2**	2.97**
	[1.33]	[2.05]	[3.08]	[3.09]	[1.10]
Pop. entering QCTs/10,000 county residents		−10.4**	−0.798	9.63**	−1.16
		[1.82]	[2.46]	[2.33]	[1.40]
Pop. exiting QCTs/10,000 county residents		−0.857	4.14**	4.99**	−0.786
		[0.761]	[1.27]	[1.44]	[0.499]
Share black	−13.0	−11.7	−89.5+	−77.8*	−8.07
	[23.3]	[23.3]	[47.5]	[38.9]	[6.66]
Share age 15–24	−55.8+	−49.0+	−139**	−90.3**	0.188
	[28.7]	[28.5]	[34.7]	[25.7]	[7.08]
Poverty rate	27.5**	24.6**	54.8**	30.2**	−2.62
	[7.19]	[7.11]	[10.3]	[8.14]	[4.42]
Log median HH income	2.67	1.33	−1.583	−2.91	−1.51
	[2.70]	[2.67]	[4.027]	[3.40]	[0.999]
Log population	−1.24	0.378	9.305+	8.93*	0.654
	[2.56]	[2.55]	[5.363]	[4.36]	[0.697]
R-squared	0.857	0.859	0.938	0.933	0.319
Observations	22,969	22,969	22,969	22,969	22969
F-statistic	22.46	19.94	84.22	75.67	3.83

Notes: Dependent variables scaled by 10,000 county residents. 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%.
* Significant at 5%.
** Significant at 1%.

erty 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.[24]

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. Fig. 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 panel A, we exclude all QCT measures, and confirm that in our fixed effects specification, county poverty rates are positively related to crime, and that conditional on poverty, crime rates are generally higher in counties with a higher median income (and greater inequality). In panel B, we include our measure of QCT coverage along with an interaction between poverty and QCT coverage.

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. In other words, one county with the same poverty rate as another but a greater fraction of its population in QCTs tends to have lower assault and robbery rates. 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 2 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 $\sqrt{22,969/5692}$ 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. Two-stage least squares 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

[24] The results are little changed when we exclude DDAs where there is no preference given under state QAPs to low-income areas. Also, when we exclude our controls for underlying churn in QCT status, we find similar but somewhat smaller average effects of contemporaneous QCT status on violent crime. This is not surprising given that counties in which a larger fraction of the population recently gained QCT status tend to have higher crime rates than counties with more stable distributions of QCTs. Similarly, the average effects for property crimes overall are smaller when we ignore differences between stable and rapidly changing counties.

Table 5
Fixed effects estimates of crime and Qualified Census Tract coverage (reduced form).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable									
	Murders	Rapes	Robberies	Assaults	Violent crimes	Burglaries	MV thefts	Larceny	Arson	Property crimes
Pop. in QCTs/10,000 county residents	0.108	0.0676	−1.10**	−5.10+	−6.02+	0.943	1.85+	0.263	2.68	5.73
	[0.0970]	[0.242]	[0.421]	[2.91]	[3.13]	[3.34]	[1.09]	[0.264]	[7.15]	[10.0]
Pop. entering QCTs/10,000 county residents	−0.0507	−0.156	0.953**	5.79*	6.54*	0.224	−1.60	0.123	−7.91	−9.17
	[0.115]	[0.241]	[0.357]	[2.68]	[2.92]	[3.02]	[1.21]	[0.526]	[5.98]	[7.97]
Pop. exiting QCTs/10,000 county residents	0.0282	0.195	−0.248	−1.48	−1.50	0.53	−2.01+	−0.463+	−4.90	−6.84
	[0.206]	[0.308]	[0.435]	[1.64]	[1.92]	[3.40]	[1.04]	[0.273]	[7.35]	[10.2]
Share black	1.67	5.34	22.0**	54.0*	83.0**	87.4	−7.32	−1.43	−211+	−132
	[1.11]	[3.47]	[6.12]	[22.1]	[25.1]	[74.9]	[23.3]	[4.29]	[111]	[168]
Share age 15–24	0.782	7.21	0.465	−33.0	−24.5	15.5	78.9	12.7	456	563
	[1.10]	[4.62]	[2.93]	[22.6]	[22.1]	[94.1]	[66.3]	[20.0]	[308]	[482]
Poverty rate	0.985+	1.61	−1.16	−11.7	−10.3	15.6	9.26	4.98	124+	154
	[0.565]	[1.68]	[1.69]	[8.93]	[9.64]	[22.0]	[13.0]	[3.56]	[75.3]	[108]
Log median HH income	0.122	0.205	0.727	1.83	2.89	−2.59	−1.20	0.535	3.23	−0.0301
	[0.198]	[0.631]	[0.586]	[3.02]	[3.34]	[4.95]	[2.12]	[0.592]	[14.0]	[17.8]
Log population	−0.0688	−0.0841	0.154	−9.44*	−9.44*	−26.2**	0.22	−0.794	−59.5**	−86.3**
	[0.198]	[0.439]	[0.529]	[4.37]	[4.52]	[9.45]	[3.54]	[0.564]	[15.7]	[25.2]
R-squared	0.307	0.582	0.932	0.802	0.854	0.825	0.887	0.435	0.884	0.889
Observations	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969	22,969

Notes: Dependent variables scaled by 10,000 county residents. 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%.
* Significant at 5%.
** Significant at 1%.

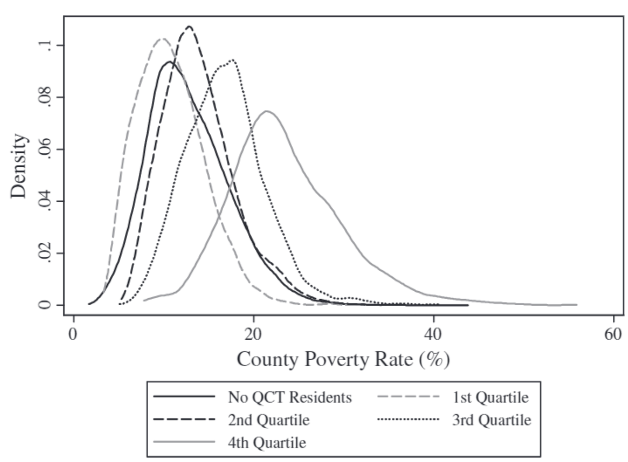

Fig. 3. Distribution of county poverty rates by population in Qualified Census Tracts.

crime. Our 2SLS estimates, which appear in Table 8, 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.[25] 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.[26] 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 new low-income housing development. Indeed, our 2SLS estimates imply that, while reducing robberies and aggravated assaults, 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 $12500.[27]

To put these figures in perspective, estimates from the U.S. Government Accountability Office (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

[25] In Tables 8 and 9, we present results from the Kleinbergen-Paap weak identification test, which is robust to the presence of heteroskedasticity. At over 50, the Kleibergen-Paap rk Wald *F*-statistics reported in Tables 8 and 9 are well above the Stock-Yogo critical values (which are close to 16 in each case).

[26] The results are little changed when we exclude DDAs where there is no preference given under state QAPs to low-income areas. Further, our results are not driven by differences inside and outside MSAs. For example, when we limit our sample to counties the 2185 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.

[27] We experimented with an alternative instrument based on the fraction of the land area in QCTs. 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. Results using this alternative instrument were qualitatively similar, but slightly smaller in magnitude. This suggests that our main results are driven by neighborhood revitalization in more densely populated areas.

Table 6
Fixed effects estimates of crime, poverty, and Qualified Census Tract coverage.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable									
	Murders	Rapes	Robberies	Assaults	Violent crimes	Burglaries	MV thefts	Larceny	Arson	Property crimes
	Panel A									
Poverty rate	0.987^{+}	1.57	−1.29	−12.6	−11.3	15.3	10.3	129^{+}	5.03	159
	[0.563]	[1.66]	[1.69]	[8.90]	[9.64]	[21.9]	[13.0]	[74.7]	[3.56]	[108]
Log median HH income	0.125	0.213	0.629	1.18	2.15	−2.78	−0.984	3.46	0.569	0.255
	[0.197]	[0.628]	[0.585]	[3.00]	[3.32]	[4.92]	[2.11]	[14.0]	[0.590]	[17.7]
Log population	−0.0907	−0.0954	0.421	-8.04^{+}	-7.81^{+}	-26.1^{**}	−0.21	-59.6^{**}	−0.847	-86.8^{**}
	[0.197]	[0.428]	[0.529]	[4.34]	[4.51]	[9.37]	[3.49]	[15.6]	[0.555]	[25.0]
Share black	1.63	5.30	22.4^{**}	55.7^{*}	85.1^{**}	86.6	−8.06	-213^{+}	−1.56	−136
	[1.11]	[3.47]	[6.14]	[22.2]	[25.2]	[74.8]	[23.4]	[111]	[4.30]	[168]
Share age 15–24	0.692	7.12	1.55	−27.5	−18.1	15.2	77.0	454	12.4	559
	[1.10]	[4.63]	[2.91]	[22.7]	[22.3]	[93.9]	[66.1]	[308]	[19.9]	[481]
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/10,000 county residents	0.144	0.217	1.70	5.45	7.52	17.4^{*}	8.23^{**}	39.8^{*}	−0.303	65.1^{*}
	[0.222]	[0.809]	[1.05]	[4.68]	[4.84]	[7.14]	[3.00]	[18.0]	[0.795]	[25.4]
(Pop. in QCTs/10,000 county residents) × poverty rate	−0.267	−1.01	-10.4^{+}	-35.0^{+}	-46.7^{*}	-72.0^{*}	-31.7^{*}	-172^{*}	1.56	-274^{*}
	[0.936]	[3.46]	[5.48]	[20.2]	[21.0]	[30.7]	[12.5]	[78.4]	[3.38]	[111]
Poverty rate	1.06^{+}	1.84	1.42	−3.49	0.82	34.1	18.6	173^{*}	4.64	230^{+}
	[0.640]	[1.68]	[1.75]	[9.15]	[10.2]	[24.4]	[15.2]	[86.1]	[3.98]	[124]
Log median HH income	0.132	0.235	0.747	1.58	2.70	−1.721	−0.5	6.24	0.571	4.59
	[0.200]	[0.630]	[0.580]	[2.98]	[3.31]	[4.99]	[2.09]	[14.4]	[0.603]	[18.2]
Log population	−0.079	−0.118	0.235	-8.75^{*}	-8.71^{+}	-26.6^{**}	−0.29	-61.4^{**}	−0.857	-89.1^{**}
	[0.198]	[0.435]	[0.533]	[4.35]	[4.51]	[9.39]	[3.50]	[15.6]	[0.560]	[25.0]
Share black	1.66	5.31	22.0^{**}	54.3^{*}	83.3^{**}	86.6	−7.87	-213^{+}	−1.48	−136
	[1.11]	[3.47]	[6.13]	[22.2]	[25.1]	[75.1]	[23.4]	[111]	[4.30]	[169]
Share age 15–24	0.754	7.12	1.31	−28.4	−19.3	17.4	78.3	456	12.4	564
	[1.10]	[4.62]	[2.92]	[22.6]	[22.2]	[93.8]	[66.2]	[308]	[20.0]	[482]
R-squared	0.307	0.582	0.932	0.801	0.854	0.825	0.888	0.884	0.435	0.889

Notes: Dependent variables scaled by 10,000 county residents. 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%
* Significant at 5%.
** Significant at 1%.

officer provides a marginal benefit of $96,000 in terms of reduced victimization each year and increases annual police expenditure by $54,000.[28]

6.2.4. Time trends

LIHTC development may be attracted disproportionately not just to QCTs, but 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 where developers anticipate further deterioration in conditions so as to ensure a sufficient supply of qualified renters.[29]

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 size and with similar trends in crime and low-income housing development prior to 2002, the first year that our instrument is identified.[30] We follow Evans and Owens (2007) and divide counties into groups based on "pre-treatment" trends and population size. For each county, we estimate a model of crimes per ten thousand residents prior to 2002 on a linear time trend, and then do the same with low-income housing units in QCTs per ten thousand residents as a dependent variable. 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 low-income housing development on crime is identified off variation in QCT status among counties of similar size and with similar trends in crime and 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 Table 8 and once again suggest that violent crimes

[28] To the extent that some developers, and in particular non-profit organizations, couple their investments with other neighborhood initiatives, our estimates may reflect the combined effect of new housing development and other associated amenities.

[29] 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).

[30] 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.

[31] The results are little changed when we use bins of different sizes, such as quartiles or deciles.

Table 7
Fixed effects estimates of crime and Qualified Census Tract coverage, 2000 and 2007.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable									
	Murders	Rapes	Robberies	Assaults	Violent crimes	Burglaries	MV thefts	Larceny	Arson	Property crimes
Pop. in QCTs/10,000 county residents	0.178	0.302	−1.15	−8.66	−9.33	6.16	3.20	0.322	12.1	21.8
	[0.369]	[0.600]	[0.838]	[5.89]	[6.32]	[6.91]	[2.03]	[0.609]	[15.5]	[21.1]
Pop. entering QCTs/10,000 county residents	1.22	0.397	−0.716	0.316	1.22	37.5	6.05	0.351	19.8	63.7
	[1.26]	[1.44]	[3.23]	[13.0]	[15.5]	[35.4]	[8.23]	[1.32]	[75.0]	[99.9]
Pop. exiting QCTs/10,000 county residents	0.257	−3.083	−6.65	−42.9	−52.4	18.0	−20.3	0.531	−28.0	−29.8
	[2.04]	[2.07]	[5.24]	[34.2]	[37.4]	[28.9]	[14.6]	[2.30]	[97.3]	[124]
Poverty rate	−0.0017	4.94	3.14	9.34	17.4	84.8	4.53	14.8	37.1	41.1
	[1.76]	[5.48]	[4.61]	[31.9]	[33.1]	[64.5]	[20.2]	[13.0]	[171]	[242]
Log median HH income	0.235	−0.143	0.299	3.78	4.17	−6.22	−0.677	−0.357	−18.8	−26.0
	[0.617]	[1.71]	[1.61]	[9.09]	[9.83]	[14.5]	[5.69]	[2.00]	[39.2]	[51.3]
Log population	−0.179	−0.317	0.287	−5.50	−5.71	−14.1	0.953	−1.25	−47.6*	−61.9*
	[0.327]	[0.802]	[0.723]	[5.03]	[5.40]	[9.36]	[3.27]	[1.32]	[18.8]	[25.3]
Share black	2.99	0.891	24.4*	34.6	63.0^{+}	56.4	−20.5	−4.86	−299^{+}	−268
	[2.03]	[4.13]	[9.55]	[33.6]	[37.8]	[102]	[30.9]	[9.91]	[174]	[262]
Share age 15–24	0.0391	9.24	−6.47	−5.43	−2.62	47.7	71.1	39.7	756	915
	[2.91]	[10.0]	[6.22]	[78.8]	[78.8]	[232]	[69.1]	[66.6]	[760]	[1120]
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

Notes: Dependent variables scaled by 10,000 county residents. All specifications include county fixed effects and 1 year dummy. Robust standard errors adjusted for heteroskedasticity and clusters at the county level in brackets.
$^{+}$ Significant at 10%.
* Significant at 5%.
** Significant at 1%.

Table 8
2SLS estimates of crime and low-income housing.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable									
	Murders	Rapes	Robberies	Assaults	Violent crimes	Burglaries	MV thefts	Larceny	Arson	Property crimes
QCT Units/10,000 county residents	0.00794	0.00499	−0.0808**	−0.377^{+}	−0.444*	0.0696	0.137^{+}	0.0194	0.197	0.423
	[0.00680]	[0.0166]	[0.0313]	[0.205]	[0.222]	[0.230]	[0.0765]	[0.0188]	[0.493]	[0.692]
Pop. entering QCTs/10,000 county residents	0.0321	−0.104	0.111	1.87	1.90	1.26	−0.584	−0.261	−2.84	−2.43
	[0.0852]	[0.174]	[0.288]	[1.36]	[1.49]	[2.14]	[0.674]	[0.196]	[3.87]	[5.60]
Pop. exiting QCTs/10,000 county residents	0.035	0.199	−0.317	−1.80	−1.88	0.283	−1.48	0.14	−7.74	−8.80
	[0.192]	[0.288]	[0.411]	[1.62]	[1.88]	[2.85]	[1.16]	[0.492]	[5.69]	[7.60]
Share black	1.76^{+}	5.40^{+}	21.1**	49.5*	77.8**	88.2	−5.72	−1.21	−209*	−127
	[1.05]	[3.25]	[5.98]	[21.5]	[24.6]	[70.0]	[22.6]	[4.09]	[104]	[158]
Share age 15–24	1.17	7.45^{+}	−3.50	−51.4*	−46.3^{+}	18.9	85.6	13.6	465	584
	[1.13]	[4.40]	[3.98]	[25.1]	[25.9]	[89.4]	[62.6]	[18.8]	[292]	[456]
Poverty rate	0.79	1.48	0.83	−2.44	0.663	13.9	5.89	4.5	120^{+}	144
	[0.539]	[16.4]	[17.1]	[10.5]	[11.4]	[21.1]	[12.0]	[3.24]	[69.3]	[100]
Log median HH income	0.112	0.198	0.834	2.33	3.48	−2.68	−1.38	0.509	2.96	−0.592
	[0.185]	[0.589]	[0.577]	[2.98]	[3.32]	[4.64]	[2.04]	[0.56]	[13.0]	[16.6]
Log population	−0.0718	−0.086	0.185	−9.30*	−9.27*	−26.2**	0.169	−0.801	−59.6**	−86.4**
	[0.179]	[0.408]	[0.504]	[4.20]	[4.39]	[8.77]	[3.36]	[0.532]	[14.7]	[23.5]
Observations	22,962	22,962	22,962	22,962	22,962	22,962	22,962	22,962	22,962	22,962
Kleibergen-Paap rk Wald *F*-statistic for weak inst.	50.37	50.37	50.37	50.37	50.37	50.37	50.37	50.37	50.37	50.37

Notes: Dependent variables scaled by 10,000 county residents. All specifications include 7 year dummies and county fixed effects. Seven 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%.

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. 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

Table 9
2SLS estimates of crime and low-income housing, including group-specific fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable									
	Murders	Rapes	Robberies	Assaults	Violent crimes	Burglaries	MV thefts	Arson	Larceny	Property crimes
QCT units/10,000 county residents	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/10,000 county residents	0.0462	−0.0287	0.0429	1.69	1.75	0.858	−0.264	−0.205	−0.749	−0.36
	[0.0894]	[0.191]	[0.285]	[1.39]	[1.51]	[2.19]	[0.697]	[0.202]	[3.87]	[5.64]
Pop. exiting QCTs/10,000 county residents	0.0223	0.228	−0.417	−2.80^{+}	−2.96	−0.775	−1.11	0.0937	−6.53	−8.32
	[0.199]	[0.294]	[0.420]	[1.67]	[1.94]	[2.91]	[1.17]	[0.498]	[5.62]	[7.42]
Share black	1.68	8.08*	18.2**	43.9^{+}	71.9**	81.9	2.18	−0.962	−116	−33.1
	[1.05]	[3.28]	[5.77]	[23.2]	[26.3]	[69.6]	[21.5]	[4.08]	[105]	[158]
Share age 15–24	1.68	7.58^{+}	−1.04	−30.4	−22.2	64.1	96.3	14.9	529^{+}	705
	[1.10]	[3.96]	[3.91]	[23.0]	[24.2]	[92.9]	[65.5]	[19.8]	[306]	[478]
Poverty rate	0.854^{+}	1.37	1.52	−4.85	−1.11	12.6	6.36	5.29	105	129
	[0.500]	[17.2]	[17.5]	[10.1]	[10.9]	[20.4]	[12.1]	[3.22]	[68.7]	[98.8]
Log median HH income	0.133	−0.0462	0.901	2.96	3.94	−3.30	−2.23	0.391	−2.94	−8.08
	[0.182]	[0.591]	[0.586]	[2.99]	[3.33]	[4.46]	[2.05]	[0.521]	[12.2]	[15.5]
Log population	−0.24	0.146	−1.27^{+}	−17.2**	−18.5**	−46.8**	−2.15	−0.585	−67.4**	−117**
	[0.210]	[0.486]	[0.753]	[5.34]	[5.56]	[9.92]	[4.20]	[0.623]	[17.9]	[28.5]
Observations	22,962	22,962	22,962	22,962	22,962	22,962	22,962	22,962	22,962	22,962
Kleibergen-Paap rk Wald *F*-statistic for weak inst.	51.88	51.88	51.88	51.88	51.88	51.88	51.88	51.88	51.88	51.88

Notes: Dependent variables scaled by 10,000 county residents. All specifications include county fixed effects and poverty and housing trend quintile-specific year fixed effects. Seven 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%.

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.[32] 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). 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 relative to 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.[33] To more directly explore the role of migration, as well as the possibility that the effects we find arise solely because of changes in the denominator of the crime rates, we examine migration patterns between counties. As part of its annual county population estimates, the Census Bureau releases components of change, including net migration (although not immigration and emigration separately). Regressions of net migration scaled by lagged population on our measure of QCT coverage controlling for other county characteristics for 2000–2007 yield no significant results.

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.

6.4. 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.

[32] Baum-Snow and Marion (2009) find evidence of significant sorting across census block groups; on average, there are close to 70 block groups per county in the U.S.

[33] According to the Current Population Survey, 67% of the entire renting population age 15 and over who moved between 2006 and 2007, and 68% of those with annual income less than $25,000, stayed within the same county.

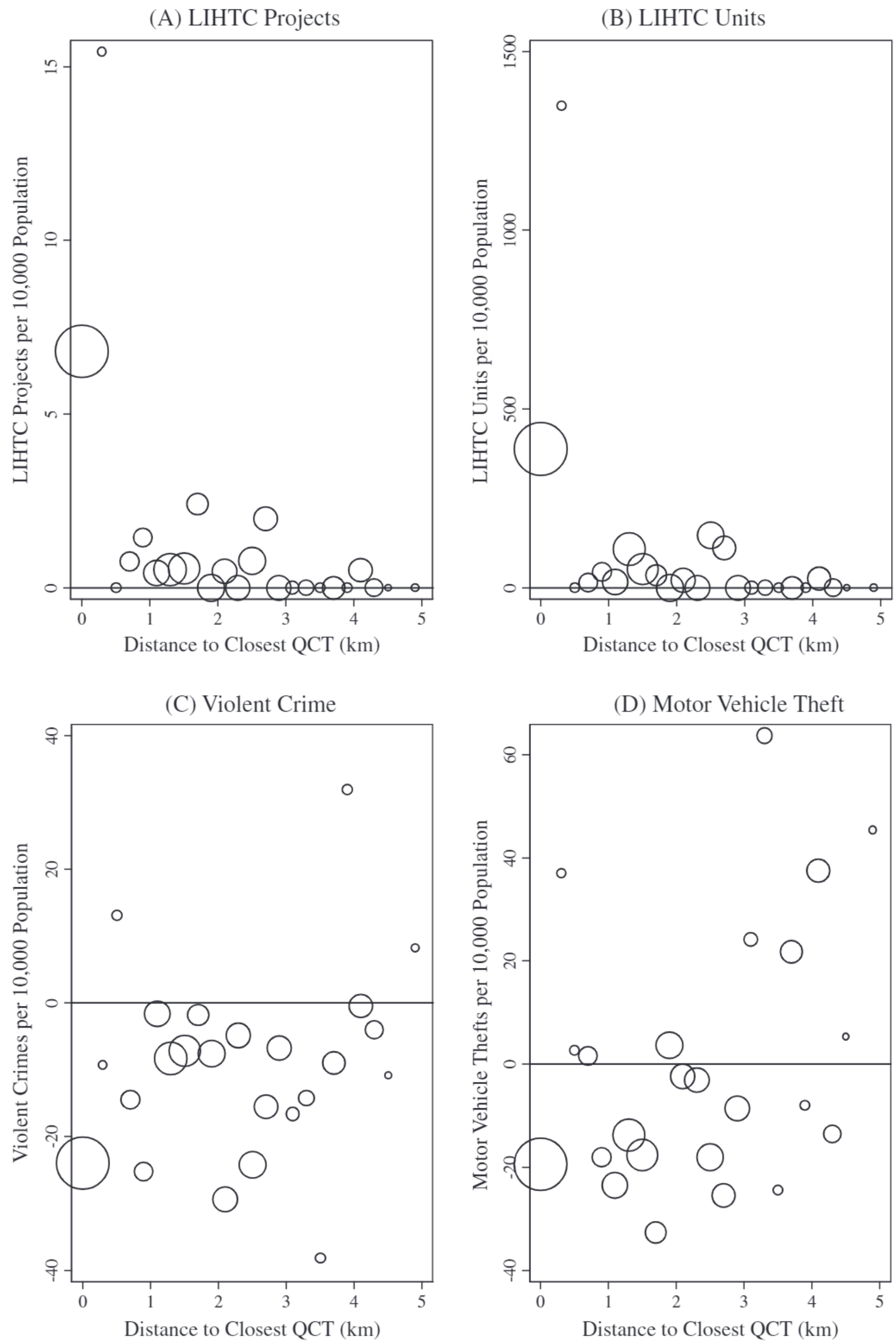

Fig. 4. LIHTC development and changes in crime rates between 2001 and 2002 within 0.2 km Bins from nearest Qualified Census Tract, Seattle.

In Fig. 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 percentage 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 0.2 km 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. Not surprisingly given the incentives to locate in qualified areas, LIHTC projects and units in Seattle are highly 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 Fig. 5, we present similar graphs for Washington, DC between 2006 and 2007, during which time the percentage 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 not entirely offset by changes elsewhere in the

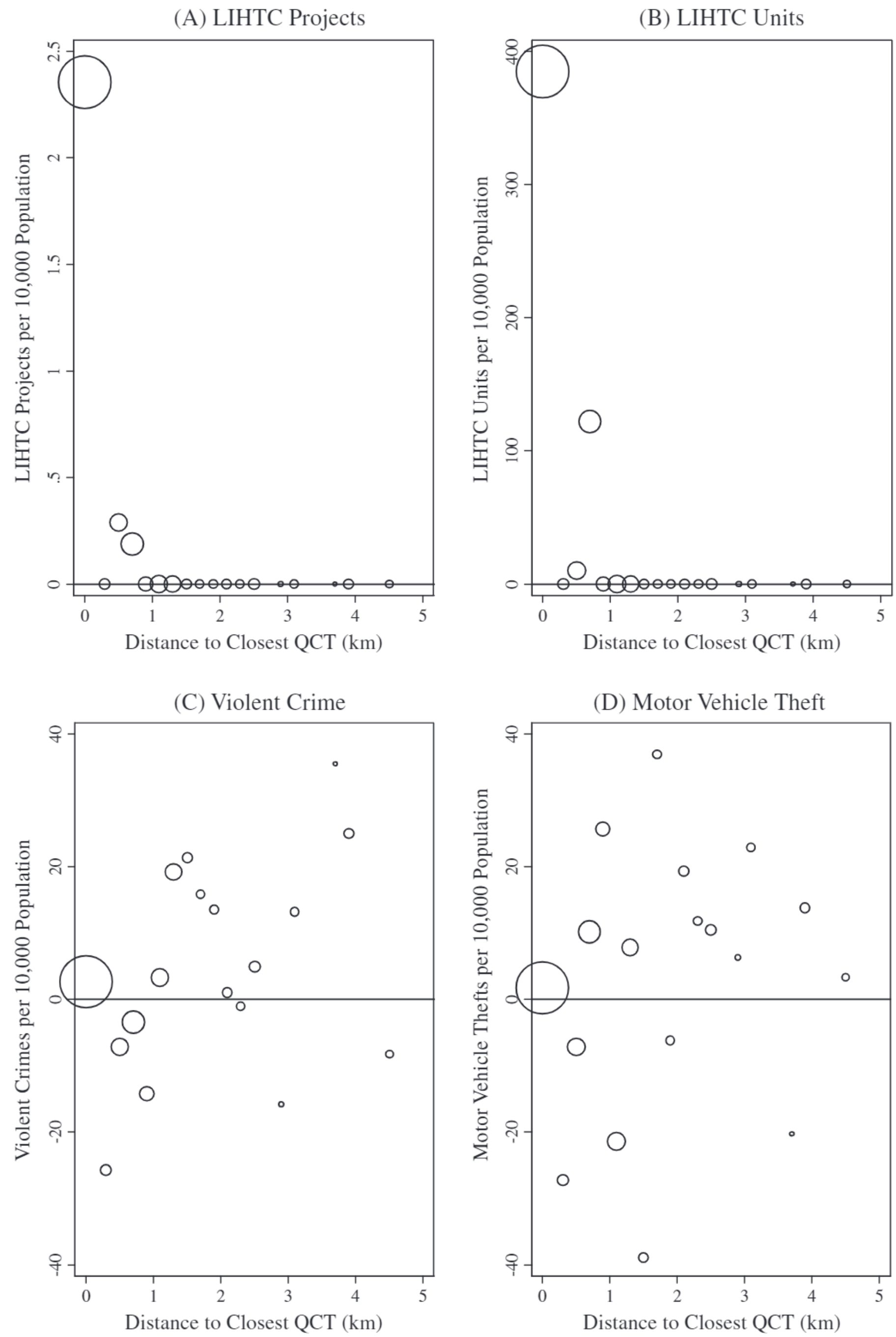

Fig. 5. LIHTC development and changes in crime rates between 2006 and 2007 within 0.2 km Bins from nearest Qualified Census Tract, Washington, DC.

county. If true, this finding runs counter to the idea that, perhaps by concentrating poverty, the LIHTC program 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. HUD's LIHTC program provides tax incentives to developers that either rehabilitate or construct rental housing in the poorest neighborhoods. Eligible 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 MSA in which the tract is located. In 2002, 2003, and 2007, changes to this formula, updates to census data, and redefinitions of metropolitan area 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 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 likely 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 direct deterrence, 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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