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Do Increases in Subsidized Housing Reduce the Incidence of Homelessness? Evidence from the Low-Income Housing Tax Credit

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Abstract:
We examine the impact of subsidized housing on homelessness using the Low-Income Housing Tax Credit (LIHTC), the largest place-based housing program in the United States. To generate quasi-experimental variation in housing placements, we exploit a discontinuous increase in the amount of tax credits available to projects placed in certain high-poverty neighborhoods. Using data from the U.S. Census and HUD, we find that LIHTC project installation has no significant impact on neighborhood homelessness but does significantly reduce county-level homelessness. Our analysis suggests that the mobility of the homeless across neighborhoods helps to explain this result. These findings are consistent with the impacts of place-based policies crossing local boundaries and homeless housing demand that is sensitive to rental prices.

JEL Classifications: **H20, H31, I32, R21, R31**
Keywords: low-income housing, tax credits, homelessness, regression discontinuity

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1 Introduction

The provision of affordable housing for low-income families is often cited by policymakers and advocacy groups as a necessity for ending homelessness (for example, Department of Housing and Urban Development (2011), United States Interagency Council on Homelessness (2010), Urban Institute (2012)).[1] The U.S. government spends a considerable amount on housing programs for the nation's poor,[2] and the use of federal housing programs to mitigate homelessness has attracted increasing interest following the recent financial downturn and housing market crisis.[3] While important for housing policy, however, whether subsidized housing is effective for combating homelessness remains an unresolved question.

The paper addresses this question by estimating the impact on the incidence of homelessness of the Low-Income Housing Tax Credit (LIHTC), the largest and fastest-growing place-based federal program for low-income housing. LIHTC provides a tax incentive for housing developers to create affordable housing by reducing the cost of projects that serve tenants who meet certain income requirements. Using data from the Department of Housing and Urban Development (HUD) and decennial U.S. censuses, we estimate the relationship between local area homeless counts and rental housing units funded by LIHTC. As a source of identifying variation, we exploit an institutional feature of the LIHTC program that generates a discontinuity in the formula that determines the amount of credits available to projects. Although tax credits are generally allocated based on project costs and the percentage of units set aside for low-income households, projects are eligible for additional tax

[1] The former president of the National Low Income Housing Coalition, Barry Zigas, stated in his 1988 statement to the Ways and Means Committee of U.S. Congress for a hearing on the Low-Income Housing Tax Credit and the role of tax policy in preserving the stock of low-income housing, "Low income people face an unprecedented housing crisis. A principal cause of homelessness is the severe lack of affordable housing for low income families."

[2] For instance, in 2011, the Department of Housing and Urban Development (HUD) spent over $34 billion on rental assistance (tenant-based and place-based), public housing operations and revitalization, and homelessness assistance grants (Department of Housing and Urban Development 2013).

[3] The Homelessness Prevention and Rapid Re-Housing Program (HPRP, a $1.5 billion, three-year federal initiative funded through the American Recovery and Reinvestment Act of 2009) was enacted to mitigate homelessness due to the Great Recession, assisting nearly 700,000 individuals in 2010 and likely preventing homelessness rates from increasing even further than observed (Department of Housing and Urban Development 2011).

credits when situated in high-poverty areas known as “qualified census tracts” (QCTs). We use the plausibly exogenous variation in tax credit allocation based on QCT eligibility to identify the effect of increased LIHTC development on the incidence of homelessness.

We find a significantly positive impact of QCT eligibility on the number of LIHTC-funded low-income units installed in a given tract, consistent with previous work (for example, Baum-Snow and Marion (2009)). However, this increase in housing infrastructure for low-income households has no appreciable impact on neighborhood homelessness, statistically or economically. Because the homeless population may be mobile, we additionally estimate the relationship between subsidized housing and homelessness at the county level and find evidence that increases in LIHTC units reduce county homelessness. Together, these results suggest that LIHTC development attracts homeless individuals to a neighborhood, thus dispersing the impact of a local housing increase more broadly. Such a result would add to a growing theoretical and empirical literature examining the extent to which the effects of place-based policies cross local boundaries (for example, Busso, Gregory, and Kline (2013), Kline and Moretti (2014)).

We also explore factors other than mobility that may affect the impact of local LIHTC development on neighborhood homelessness. First, examining proxies for the housing quality of the housed, we find limited evidence that LIHTC units are allocated in part to individuals previously in lower-quality housing. Second, we examine whether there are spillovers across neighborhoods in the supply of LIHTC housing. We find a negative correlation of low-income housing development across tracts that is quite modest, suggesting that such supply spillovers do not account for the fact that subsidized housing has no significant effect on homelessness at the neighborhood level. Lastly, we develop a supply-demand model to further examine the mechanisms that could drive the non-mobility effect of subsidized housing on homelessness. Our model allows for the influence of various parameters, including the crowd-out of housing that would otherwise have been provided by the private sector (Baum-Snow and Marion (2009); Eriksen and Rosenthal (2010); Malpezzi and Vandell (2002); Sinai and Waldfogel

(2005)), the price elasticity of homeless housing demand, the extent of LIHTC allocation to the homeless rather than the already housed, and the aforementioned spillovers in low-income housing supply across neighborhoods. Our results imply that the local housing demand of homeless individuals and those on the margin of homelessness may be sensitive to housing prices, with demand elasticities larger than those of the non-homeless in other studies (Hanushek and Quigley 1980).

Our study contributes to the literature that examines, with mixed evidence, the effect of subsidized housing on homelessness. Early (1998) uses homeless count data from a 20-city, 1987 Urban Institute survey matched to data on the housed poor from the American Housing Survey to estimate the impact of city characteristics on the probability of being homeless. He finds that subsidized housing programs are not effective at reducing homelessness, due to a lack of targeting to the homeless. Early and Olsen (2002) use homeless counts from the 1990 Decennial Census and find nonrobust evidence that subsidized housing reduces homelessness rates. Troutman, Jackson, and Ekelund (1999) combine the 1990 Census data with data from a 1984 HUD survey and find positive effects on homelessness of federal spending on low-income housing. They argue that the replacement of affordable housing for the sheltered poor with federally assisted housing creates perverse incentives to become homeless. Moulton (2010) utilizes recent point-in-time estimates of the homeless population produced by HUD and finds that increases in federal homeless funding are correlated with reductions in chronic homelessness.

A related literature examines the effect of housing market conditions, more generally, on the incidence of homelessness. Honig and Filer (1993) find a strong correlation between housing cost measures (rent at the 10th percentile and vacancy rates) and homelessness, using the 1984 HUD survey. Quigley, Raphael, and Smolensky (2001) examine the incidence of homelessness using four data sources, two of which are nationally representative (including 1990 Census data) and two of which are California-based. They find that small increases in affordable housing (higher vacancy rates and lower median rents) may significantly reduce the rate of homelessness. Studies that have highlighted the effect of rent control laws on homelessness find either no statistical effect (Early and Olsen 1998) or a slightly positive effect (Grimes and Chressanthis 1997).

This paper improves upon this earlier work by using more reliable, nationally representative data, by focusing on a large and growing subsidized housing program, and by employing a more credible identification strategy. By utilizing exogenous variation in federal funds through QCT eligibility rather than cross-sectional correlations, we more plausibly identify the causal effect of such funds on the incidence of homelessness. A few studies have used the variation generated by QCT determination to identify the impact of LIHTC on other outcomes like the stock of low-income housing, homeowner turnover rates, and property values (Baum-Snow and Marion 2009), crime (Freedman and Owens 2011), as well as poverty concentration and neighborhood inequality (Freedman and McGavock 2015).

The remainder of the paper is organized as follows: Section 2 provides an overview of the LIHTC program. Section 3 describes the estimation strategy and data used for analysis, while Section 4 presents the main results. Section 5 discusses possible mechanisms for our findings not already explored in the main results, and finally, Section 6 concludes.

2 Overview of the Low-Income Housing Tax Credit

LIHTC is a tax incentive that was created under the Tax Reform Act of 1986 and benefits affordable rental housing developments targeted at low-income households. In general, credits are allocated annually to state housing authorities based on state population and are then distributed to private developers through a competitive process. These credits are non-refundable and can either be used to offset the developer's tax liability or, as is most often the case, sold to generate capital. Taxpayers who own LIHTCs can claim a dollar-for-dollar reduction in tax liability over 10 years.

To qualify for the credit, a project must meet certain criteria over tenant incomes for a subset of units. Specifically, either at least 20 percent of the units must be rent-restricted and occupied by individuals whose income is 50 percent or less of area median income (AMI), or else at least 40 percent of the units must be rent-restricted and occupied by individuals whose income is 60 percent or less of AMI, where "area" is defined by the relevant metropolitan statistical area (MSA).[4]

The tax credit amount that a project may receive depends on several factors. A project's qualified basis for the credit is determined by multiplying the "eligible basis," or the costs that are eligible to receive the credit,[5] by the percentage of units that are allocated to households below the specified income limit. Credit allocations are determined by applying the appropriate credit rate to this qualified basis. There are two credit rates that can apply. The credit rate is equal to a percentage of the cost of development, either up to 70 percent or up to 30 percent of incurred costs in present discounted terms. Projects for new construction and the cost of rehabilitating a building (if not also funded by tax-exempt bonds) are eligible for the 70-percent credit. The cost of acquiring a pre-existing building and projects that are partially funded with tax-exempt bonds are eligible for the 30-percent credit.[6]

While credit allocations generally follow a formula based on project characteristics, there is a deviation allowed from this rule. Under the Omnibus Reconciliation Act of 1989, new legislation provided additional incentives to develop LIHTC projects in certain very-low-income areas, designated as "qualified census tracts" (QCTs). A tract where at least 50 percent of households have incomes below 60 percent of AMI is eligible to be deemed a QCT.[7] A project placed in a designated QCT receives an additional 30 percent boost to

[4]Tenant incomes must be initially certified to demonstrate eligibility and are subject to annual recertification, with the exception of projects that are 100-percent LIHTC units (see HUD informational page, "Certifying Tenant Incomes" at http://www.hud.gov/offices/cpd/affordablehousing/training/web/lihtc/eligibility/incomes.cfm). Additionally, HUD follows the Office of Management and Budget definitions of metropolitan areas, with some exceptions. AMI estimates for all metropolitan areas and counties are made using data from the decennial census, American Community Survey, Internal Revenue Service, and the American Housing Survey.

[5]These are typically the non-land acquisition costs and construction costs of the project.

[6]Annual credit rates are typically around 9 percent or 4 percent; actual percentages are determined monthly by the Internal Revenue Service.

[7]The relevant income threshold for each tract is adjusted according to the average household size in the tract. AMI is decreased by 10 percent for every fewer person than four in the average household, and

its qualified basis. Because of this allocation rule, observationally similar census tracts may face distinct tax credit benefits for LIHTC-funded projects due to differences in QCT status. QCT eligibility is the source of variation we exploit to identify the impact of the LIHTC program on homelessness, using a regression discontinuity framework.

Although the concept of QCTs was created for purposes of the LIHTC program, QCT status is also one of the criteria that can determine whether an area is in a historically underutilized business zone (HUBZone).[8] The HUBZone Empowerment Contracting Program was enacted into law as part of the Small Business Reauthorization Act of 1997 to encourage economic activity and employment growth in designated HUBZones by providing preferences and access to increased federal contracting opportunities (United States Small Business Administration 2011). We discuss potential concerns for our identification strategy from this additional role of QCT status and how we address such concerns in Section 3.

3 Methodology and data

3.1 Estimation strategy

Our goal is to estimate the impact of the installation of nearby LIHTC units, L, on the number of local area homeless, H. We therefore seek to estimate the following general specification for neighborhood i:

$$H_i = \beta_0 + \beta_1 L_i + \mathbf{X}_i'\theta + \varepsilon_i, \tag{1}$$

increased by 8 percent for every additional person beyond four. Corresponding adjustments are made for non-integer tract average household sizes above or below four. Not all census tracts that meet the requirements for QCT status are designated QCTs because at most 20 percent of a metropolitan area can be designated qualified. When more than 20 percent of the population of a metropolitan area resides in eligible tracts, tracts are ranked according to the fraction of households that meet the income criterion and are designated as QCTs until the 20 percent threshold is met. Baum-Snow and Marion (2009) show that this restriction is not particularly binding, as 96 percent of QCT-eligible tracts in their data are classified as QCTs. The method for distinguishing QCT status has changed since 2000 to incorporate poverty rates as well, but that rule change is not applicable to this study.

[8] In addition to QCT status, an area can be designated as a HUBZone if it is any one of the following: a Qualified Nonmetropolitan County, a Qualified Indian Reservation, a Qualified Base Closure Area, or a Redesignated Area (United States Small Business Administration 2011).

where $\mathbf{X}$ is a vector of control variables containing other relevant neighborhood characteristics that may affect the number of homeless individuals or LIHTC development. The parameter of interest is β_1, which indicates the impact of an additional LIHTC unit on an area's homeless count. If low-income housing reduces homelessness, then β_1 should be negative. We specify our dependent variable as the homeless count rather than the rate so that our assumption of linearity and a constant marginal effect β_1 is more likely to hold.[9]

There are several reasons why the number of low-income housing units in an area may be endogenous to the number of homeless. Unobservable neighborhood characteristics or preferences of residents that influence homelessness are likely to be correlated with LIHTC project placement, which is a combination of both having applied for the credit and having received approval of the project application. Moreover, the homeless population itself may factor into LIHTC project placement decisions. Thus, ordinary least squares (OLS) estimates of equation (1) will tend to be biased.

To identify the causal effect of low-income housing on the number of homeless, we exploit the discontinuity in the probability that a project receives additional tax credits through the QCT eligibility of its census tract. Recall that when at least 50 percent of households in a tract have incomes below 60 percent of adjusted AMI, the tract is eligible to be a QCT and is generally designated as such.[10] We therefore employ a fuzzy regression discontinuity (RD) design and instrument for the number of low-income housing units placed in an area, with an indicator for whether the tract is QCT-eligible. The first-stage equation for the number of low-income housing units in an area is given by:

$$L_i = \gamma_0 + \gamma_1 QCT_i + \gamma_2 f(elig_i) + \mathbf{X}_i'\psi + u_i, \tag{2}$$

where QCT indicates the QCT eligibility of a tract and $f(elig)$ is a function of the running

[9] Nevertheless, baseline population (log) is included in $\mathbf{X}$, and throughout the paper we discuss the implications of our results for the homelessness rate in the average neighborhood.

[10] Because at most 20 percent of a metropolitan area's population can live in qualified tracts, as previously described, the probability of being designated a QCT does not jump discretely from 0 to 1 at the threshold of 0.5.

variable, *elig*, which is the fraction of households in a tract that meet the relevant income requirement. The QCT indicator equals 1 if $elig \geq 0.5$, and 0 otherwise. Meanwhile, u is a mean-zero error term. Given the incentives for LIHTC development in QCTs, we expect γ_1 to be positive.

The covariates in $\mathbf{X}$ are included to capture heterogeneity across census tracts that may affect homelessness or LIHTC development. The demographic characteristics we include are the 1990 homeless count, the log of median household income, the log of total population, average household size, share of blacks, share of Hispanics, share of females, share married, share of population aged 16 to 24, share of population by education category, and the poverty rate. Housing market characteristics included are the log of median rent and rental vacancy rate. These variables are all measured at the census tract level. Because QCT status is used to determine HUBZones, we also include a tract's unemployment rate as a control variable. Consistent estimation requires that for otherwise similar neighborhoods, the homeless population does not utilize QCT eligibility when determining where to locate.[11] Even with our controls, individuals with similar preferences or other unobservable characteristics may choose to locate in the same area, inducing a correlation in the error terms of census tracts in those areas. Therefore, in all estimation unless noted otherwise, we include MSA fixed effects, and we cluster standard errors by MSA to allow for an arbitrary variance-covariance structure within a metropolitan area.[12]

In our RD design, consistent estimation of β_1 comes from a strongly nonzero γ_1 and from the assumption that there are no unobservable characteristics that affect homelessness that also cause nonrandom sorting in census tracts across the QCT eligibility threshold. As Baum-Snow and Marion (2009) discuss, such sorting generally seems unlikely to occur. First, since QCT status was updated in 1993 using the 1990 census, individuals could not know in

[11]Such homeless location choice would bias our instrumental variables (IV) estimates towards OLS. Due to the LIHTC and HUBZone programs, QCT eligibility (or status) may be indicative of housing and labor market growth and thus affect the location decisions of homeless individuals at the margin of otherwise similar census tracts. We examine this homeless mobility concern in Section 5.

[12]Because some MSAs span states but unobservables may vary at the state level, we treat the portions of the MSA in each state as distinct in these cases.

1990 which tracts would or would not be deemed QCT-eligible within a few percentage points of the 50-percent threshold. Secondly, even if some individuals had perfect information on the composition of the relevant census tracts, the census sampled only one in six households for the long-form survey, thereby inducing substantial sampling variation.

One concern for our tract-level analysis is that the homeless population, which may be mobile, could be attracted to areas with increased LIHTC development. Even in the short run, daily mobility of the homeless can exceed the distance covered by a census tract (Jocoy and Del Casino Jr. 2008), and there is evidence that the homeless are more likely to migrate to neighborhoods with available low-income housing and associated services than to other areas.[13] Moreover, national statistics suggest that the situation of the overwhelming majority of the homeless is not chronic.[14] The housing demand and related mobility of the homeless whose situation is not chronic may be more responsive than that of the chronic homeless to changes in the affordable housing market. More generally, it has been theorized that the impact of place-based policies like LIHTC is affected by migration, which may offset local effects.[15] Thus, tracts with low levels of LIHTC activity may not be appropriate counterfactual examples for tracts with high levels of LIHTC activity, because of inter-tract migration.

To examine this concern regarding mobility, we examine the relationship between LIHTC development and homelessness in a larger geographic area. We assume that spatial relocation of the homeless on the basis of LIHTC development (or QCT eligibility) may occur across

[13] Jocoy and Del Casino Jr. (2008) find that respondents cite a lack of affordable housing or services as among the top reasons for leaving the city in which they first became homeless. Glaeser, Kahn, and Rappaport (2000) similarly find that access to services like public transportation influences location decisions of the poor. Additionally, this relocation decision could even be initiated or assisted by the local government.

[14] In 2011, non-chronic homelessness accounted for 83 percent of total U.S. homelessness (Witte (2012)). During our sample period, HUD defined chronic homelessness as "an unaccompanied homeless individual with a disabling condition who has either been continuously homeless for a year or more or has had at least four episodes of homelessness in the past three years." It was not until the 2009 Homeless Emergency Assistance and Rapid Transition to Housing Act that this definition was amended to include families (Witte (2012)).

[15] For a recent discussion and survey of the theory, see Kline and Moretti (2014). Recent examples of empirical work include Freedman and Owens (2011), who discuss potential residential displacement in the context of LIHTC's impact on local area crime, and Busso, Gregory, and Kline (2013), who examine the extent of such relocation when assessing the welfare impact of the Empowerment Zone program.

tracts but not across counties. If this assumption holds, then county-level estimates do not suffer from the location choice issues affecting tract-level analysis. We re-run our analysis at the county level rather than the tract level, assuming that county IV estimates are consistent and that they exclude changes in the homeless count resulting from mobility-driven changes in the composition of a tract (that is, the extent to which it is inhabited by the homeless vs. the non-homeless). Only changes in homelessness due to adjustments in housing status should be observed. Because QCT eligibility is designated at the tract level and not the county level, we use the number of tracts in a county that are QCT-eligible to instrument for county-level LIHTC development.

To ensure consistent county-level IV estimates, analogous to identification at the tract level, the ideal experiment is to compare two equally sized counties with the same number of tracts, N, and with very similar poverty distributions. In particular, these counties would be identical in $(N-1)$ tracts but differ slightly in the Nth tract, resulting in a difference of one QCT-eligible tract across the two counties.[16] This ensures that the counties would differ in LIHTC development based exogenously on the difference in QCT-eligibility in those otherwise-identical Nth tracts, rather than based endogenously on unobserved differences in poverty that might also affect homelessness. To implement this experimental ideal in county-level estimation, we include controls for county size via the log of total population and the log of tracts in the county. We also try to control for the distribution of county-level poverty. The poverty controls include a third-degree polynomial analog of the tract-level running variable based on the number of "eligible" households in a county,[17] county-level analogs of all other tract-level controls, and additional higher-order terms for some controls.[18]

[16]Specifically, assume that in $(N-1)$ tracts across the two counties, the fraction of eligible households is identical, resulting in $J \leq (N-1)$ QCT-eligible tracts in each county. In the last, Nth, tract, both counties again have a similar fraction of eligible households. However, one tract is QCT-ineligible, falling just below the relevant threshold, while the other tract is QCT-eligible, falling just above the threshold. Thus, while one county has J QCT-eligible tracts, the other county has $(J+1)$ QCT-eligible tracts.

[17]Since qualified status is determined at the tract level, there is no true eligibility at the county level. However, the variable remains a valid measure of poverty at any level of geographic aggregation.

[18]We experimented with different combinations and functional forms for the higher-order control variables, using fit and first-stage strength as a guide for the preferred specification. Additionally, county analogs of tract variables are defined identically but measured at the level of the county rather than the tract. The

Due to greater variation in area population at the county level, there may be increased heteroskedasticity of the estimation errors relative to our tract-level analysis, which is confirmed by diagnostic testing.[19] To account for this, along with continuing to include clustered standard errors, we weight OLS and IV analysis by 1990 county population. The sample for county estimation includes the same areas (that is, both urban and rural) as tract-level analysis, in order to maintain consistent spatial coverage.

3.2 Description of data

Data for our analysis come from several sources. First, we use homeless counts from the 2000 Decennial U.S. Census, which provides a large and recent source of aggregate, cross-sectional data.[20] The Census Bureau conducted its Shelter and Street Night, or "S-Night," efforts to enumerate persons sleeping in a wide range of facilities that serve the homeless as well as persons visible at street locations. Counts of those living in shelters were conducted on March 27, 2000, and counts of those living in designated streets on March 29, 2000. In Section 5, we also use total population and several proxies for the housing quality of the housed population from the 2000 Census.

Data on LIHTC developments come from HUD's LIHTC Database.[21] The database contains information on projects placed in service between 1987 and 2009. We utilize information on project location, the year the project was placed in service, the number of units,

sole exceptions are the log of household median income and the log of median rent. Due to missing census data at the county level, these variables are the unweighted county means of the tract-level variables, rather than direct county-level measurements.

[19] Such increased heteroskedasticity is not necessarily the case (Dickens 1990). As a diagnostic, we compare weighted and unweighted IV estimates at the tract and county levels. At both levels, weighted coefficients are similar to unweighted estimates, falling within 95 percent confidence intervals of the former (for example, for new construction units, the weighted tract-level IV estimate is -62.29). This suggests that our estimation is correctly specified and eliminates motivation for weighting unrelated to heteroskedaticity (Solon, Haider, and Wooldridge 2015). However, while standard errors from weighted estimation, compared with unweighted, are slightly larger at the tract level, they are much smaller at the county level (for example, for new construction units, the unweighted county-level IV standard error is 226.92).

[20] These data are obtained from from the National Historical Geographic Information System (Minnesota Population Center 2011) and are available at `nhgis.org`.

[21] The database is available at `lihtc.huduser.org`.

and the type of project.[22] The database also provides information on whether the census tract for the development is a QCT.[23]

We restrict our analysis to projects that were placed into service between 1994 and 1999 for two reasons. First, we focus on projects in tracts whose QCT status determinations were based on information in the 1990 Decennial Census, and 1994 was the first full year in which this was the case.[24] Second, because we examine homelessness as recorded in the 2000 Census, we assume that projects that were placed into service after 1999 have no impact on our outcome of interest. Between 1994 and 1999, there were 8,660 LIHTC projects placed into service, of which 8,132 projects contain census tract identification.[25]

To determine each tract's QCT eligibility, we obtained data used by HUD based on the 1990 Census.[26] We computed the proportion of households in a tract that fall below the relevant MSA income threshold. We then predicted actual QCT status using additional information on the population and ranking of QCT-eligible tracts in an MSA (see section 2).[27]

We use additional, baseline tract characteristics that may be determinants of neighborhood LIHTC development or homeless counts from the 1990 Decennial U.S. Census (Min-

[22]The database also contains some information on the attributes of the targeted population for the project. One targeted population is the homeless, which represents a very small 3.7 percent of projects in the database with nonmissing target information (or 1.4 percent of all projects). We examine the effect of such targeting for our results later in Section 5.

[23]Ideally, we would also examine LIHTC tenant characteristics, such as former homelessness, in further detail. Unfortunately, until recently there was no federal mandate requiring the collection of such tenant data, causing little to be known about the characteristics of LIHTC residents (Horn and O'Regan 2011). Given this restriction, Horn and O'Regan (2011) collect data on a limited sample (Massachusetts, Texas, and Delaware) in order to examine the racial composition of LIHTC tenants. They note that, as of 2009, states are now required to collect and provide some tenant data to HUD.

[24]QCT status of tracts remains constant over the 1994–1999 period.

[25]There are between 1,263 and 1,468 projects placed into service each year, representing a total of 526,436 units and 486,206 low-income units. Originally, 779 projects are missing census tract information. For these projects, we utilize address information in the HUD database to try to determine the appropriate tract designation. We successfully recover 251 projects in this manner.

[26]We are grateful to Matthew Freedman and Emily Owens for providing us with these data, as well as code for determining QCT eligibility.

[27]Because the LIHTC Database contains HUD's QCT designations, we verified that our QCT predictions are the same as those in the database, to be confident we are accurately determining QCT eligibility and status. Our QCT predictions matched HUD's QCT designations for all but one project.

nesota Population Center 2011).[28] We collected tract-specific information on household income, household size, population, race and ethnicity, gender, marital status, age, education, unemployment rates, poverty rates, median rent, and rental vacancy rates.[29] The 1990 Census also contains counts of the homeless population that we use, although the methodology for enumerating the homeless changed between 1990 and 2000 (Smith and Smith 2001). The homeless count recorded in the 1990 Census is included in $\mathbf{X}$, so estimated coefficients measure the impact of covariates on the change in homeless counts relative to 1990 levels, which may also help reduce bias.[30] Because of the change in the methodology of counting the homeless, inclusion of 1990 homelessness as a control is preferred over directly transforming our dependent variable to the decadal change in homeless counts.[31] In Section 5, when proxies for the housing quality of the housed population in 2000 are the dependent variables, we include 1990 measures of these variables as controls instead of 1990 homelessness.

While the LIHTC database contains both 1990 and 2000 census tract identification for a given project based on its address, for tracts where no LIHTC development occurs, we use the Census Bureau's 2000 Census Tract Relationship Files to match 1990 census tracts to 2000 census tracts.[32] For the tracts we are able to match across the two censuses and the rest of our sources, we aggregate the combined data up to the census tract level, resulting in 31,573 tract-level observations, of which 30,933 have nonmissing values of all variables and are in our estimation sample with all observations.

[28] The data are available at `nhgis.org`.

[29] Due to measurement error, in some 1990 Census tracts the proportion of the tract population calculated to be in a particular demographic category was greater than 1. As the number of such observations never exceeded 0.6 percent of all 61,349 1990 Census tract observations that we examined, we censored such values at 1 in our data.

[30] We thus estimate the impact of the flow in LIHTC projects from 1994 to 1999 on the decadal flow in homeless counts. If LIHTC unit installation is correlated with time-invariant area unobservables, adding 1990 homelessness to the model reduces estimation bias.

[31] The transformation imposes the restriction that the coefficient on 1990 homeless counts in equation (1) equals one, which may not hold given the measurement differences across census years.

[32] The data are available at `census.gov/geo/www/relate/rel_tract.html`. Some census tracts change geography over the 1990–2000 period. Because our estimation strategy is based on being able to determine the proportion of low-income households in a tract and QCT eligibility, which in turn are based on 1990 Census information, we restrict our sample to tracts whose geography either exhibited no change or a split. We drop tracts that merged or otherwise revised boundaries over the decade. All tract-level statistics and analysis are calculated based on 1990 tract boundaries.

Table 1 presents summary statistics for our data. Importantly, for most of the included demographic and housing characteristics, there is no discontinuity across the policy threshold. Only the share aged 16 to 24, the unemployment rate, and the share with a high school degree are statistically different at the 5-percent level, and the magnitudes of these differences are quite small. On average, compared with QCT-ineligible neighborhoods, eligible areas are poorer, with larger minority populations, higher unemployment and poverty rates, lower levels of educational attainment, and more LIHTC activity. Our estimation strategy exploits the exogenous variation in LIHTC development that occurs in the vicinity of the QCT eligibility threshold. Thus, we estimate the causal relationship between low-income housing and homelessness for these moderately poor neighborhoods around the eligibility cutoff.

3.3 Measurement Error

Given the inherent difficulties in accurately counting the homeless population, measurement error is a potential concern.[33] To consider the impact on our estimates of measurement error in our dependent variable, suppose that the observed homeless count, H^*, is given by $H_i^* = \lambda H_i + \omega_i$, where H is the true, unobserved homeless count and ω is measurement error. Given equation (1), the observed homeless count can be rewritten as:

$$H_i^* = \beta_0\lambda + \beta_1\lambda L_i + \mathbf{X}_i'\theta\lambda + \varepsilon_i^*, \tag{3}$$

where $\varepsilon_i^* = \lambda\varepsilon_i + \omega_i$. If $\lambda = 1$, β_1 is estimated consistently with valid IV estimation but with decreased precision due to larger errors. However, we are particularly concerned that $\lambda < 1$, which would cause attenuation bias to contribute to small estimated effects of LIHTC development on homelessness.

Ideally, we could use a large-scale validation study on the 2000 Census S-Night homeless

[33] While classical measurement error would lead to less precise estimates of LIHTC's effect on homelessness, nonclassical measurement error could bias our estimates, with the bias going in either direction.

counts to estimate λ. While no such study exists, we utilize data from a small-scale validation study on the 1990 Census S-Night to inform the nature of this potential bias. The consensus view is that the 1990 S-Night effort notably undercounted the homeless, with the Census Bureau's estimate of 230,000 homeless individuals being approximately one-half the magnitude of other national estimates (Quigley, Raphael, and Smolensky 2001). To assess the quality of the S-Night enumeration, the Census Bureau sponsored research in five cities where "decoys" were positioned at various street locations to determine the extent of such mismeasurement (Martin 1992). The proportion of decoys that were not counted provides a rough estimate of the degree of undercounting across the five cities (Quigley, Raphael, and Smolensky 2001).

The validation study yields a positive correlation of 0.43 between undercounting rates and observed homeless counts across the five metropolitan areas.[34] If this pattern holds across all MSAs and is similar for the 2000 S-Night enumeration, then this suggests that $\lambda < 1$. Using the undercount rates to inform us about the magnitude of the measurement error, we obtain an estimate of $\hat{\lambda} = 0.836$, which implies that our estimates of LIHTC's impact on local homelessness are somewhat biased towards zero.[35] We obtain an approximate correction for this bias by scaling up our estimates by a factor of $1/\hat{\lambda} = 1.196$, or 19.6 percent. We examine the impact of measurement error on our results as we present them.

[34]The percentages of decoys not counted was 10 percent in New Orleans, 10 percent in Phoenix, 13 percent in Los Angeles, 20 percent in New York, and 25 percent in Chicago (Martin 1992). Meanwhile, the estimated homeless counts in 1990 based on S-Night were 569 in New Orleans, 1,277 in Phoenix, 5,843 in Los Angeles, 21,986 in New York, and 3,210 in Chicago.

[35]With a value of $\lambda < 1$, the impact of measurement error on estimate precision is less clear, as this depends on how ε^* compares with ε.

4 Results

4.1 First stage

Before turning to our main specification, we present results from our first stage regressions in Table 2. Each column represents estimates for one of four measures of LIHTC development: the number of LIHTC-funded units, the number of units set aside for low-income households, and these measures focused on new construction projects only. Each cell provides an estimate of γ_1 for a different specification of equation (2). Unless stated otherwise, we include a cubic polynomial of the running variable to allow for sufficient flexibility.[36] For our baseline specification, we focus on census tracts where the share of the eligible population is between 25 and 75 percent. In specifications 2–4, we adjust the window of the running variable for tracts included in our estimation sample. In specifications 5–8, we conduct placebo tests where we consider alternative thresholds for determining QCT eligibility to verify the validity of our RD design.

In the baseline specification, the impact of QCT eligibility on LIHTC outcomes for otherwise similar neighborhoods is universally positive, as expected, if additional tax credits lead to more development. The impact of QCT eligibility is both relatively large and stronger for new construction development than for rehabilitation projects, which is consistent with other studies (for example, Baum-Snow and Marion (2009), Freedman and McGavock (2015)).[37] A QCT-eligible area receives, for instance, 6.4 more new construction units than an otherwise similar ineligible tract. Given that the average number of new construction units in a tract is 9.7, this constitutes a 66 percent increase. Similarly, QCT eligibility increases new con-

[36]We experimented with different functions of the running variable, from a linear function to a sixth-degree polynomial. Results are similar across specifications.

[37]New construction projects account for the majority of LIHTC projects placed into service in our sample. Because new construction projects generally receive a higher credit rate than rehabilitation projects, the impact of an increased basis through QCT status is larger for new construction developments. Another measure of LIHTC development that could be considered is the number of projects that are funded by the credit. The effects of QCT status on the number of projects placed in a tract are not statistically significant, however, indicating that additional benefits of locating a LIHTC project in a QCT do not induce developers to engage in more projects, but rather to expand the size of existing projects by adding units.

struction low-income units by 58 percent (that is, a 5.1 unit increase relative to an average of 8.8).

To better understand what these first-stage estimates imply for the potential impact of LIHTC development on homelessness, note that the average census tract in 2000 had a population of 5,241 and a homelessness rate of 0.7 percent, equivalent to 37 homeless individuals. Under the extreme assumptions that all of the additional 6.4 new construction units received by QCT-eligible tracts are allocated to the homeless, and that the homeless occupy units at the same rate as the non-homeless (that is, 2.62 individuals per unit), then LIHTC development would lead to $6.4 \times 2.62 \approx 17$ fewer homeless people. Thus, our first-stage results would imply a 45 percent reduction in the homelessness rate to 0.4 percent. This exercise suggests that there is scope for a large effect of QCT eligibility on homelessness through increases in LIHTC development.[38]

The first-stage results are illustrated in Figure 1, which plots predicted values of the cubic control functions and average values of LIHTC development variables within percentage point bins against the fraction of eligible households. The left column reflects all LIHTC development, while the right column reflects new construction development only. The remaining specifications in Table 2 confirm the validity of our first-stage estimation. When adjusting the window of the running variable, point estimates are generally consistent with our baseline specification. Additionally, as expected, the discontinuity in LIHTC activity based on placebo eligibility thresholds is typically not statistically different from zero.

4.2 Main specification

Table 3 provides results from equation (1), focusing solely on the two new construction unit-based measures of LIHTC development where credible IV estimation is plausible.[39] Columns

[38]See Section 5 and the appendix for a more in-depth, refined version of this exercise that reflects a formalized model.

[39]Stock and Yogo (2005) provide critical values for partial F-statistics on the exclusion restriction to help test for the presence of weak instruments. Critical values for the maximal actual size of a 5-percent Wald test of $\hat{\gamma}_1 = 0$ are 16.38, 8.96, and 6.66 for maximal test sizes of 10, 15, and 20 percent, respectively. The

(1) and (2) provide our IV regression results, where LIHTC development is instrumented with QCT eligibility. The point estimates suggest that the increase in low-income housing associated with QCT-eligibility may reduce homelessness, but these effects are not statistically different from zero. Thus, we are unable to reject the null hypothesis that LIHTC development has no effect on neighborhood-level homelessness. Figure 2 provides further evidence of the reduced-form relationship between homelessness and QCT eligibility. Plotted in the figure are predicted values of the cubic control functions and average values of the number of homeless (as well as homelessness rates) within percentage point bins against the fraction of eligible households. Once again, we observe no evidence of a decrease in homelessness at the eligibility threshold.

If we take the magnitudes of the estimated effects seriously, the impact of LIHTC on homelessness is also not economically significant. For instance, an increase of 100 new construction units, 10 times the amount in the average tract, is estimated to decrease the homeless count by 18.3 individuals. Thus, in order to get a 10-percent reduction in the homeless count in the average tract (2.2 fewer individuals), new construction units would have to more than double in number. Considering this effect in terms of homelessness rates rather than counts yields qualitatively similar conclusions.[40]

Accounting for measurement error does not affect the economic importance of our results. Focusing on Table 3 column (3), our coefficient estimate would change very slightly with the bias correction, from -18.32 to -21.91. Thus, the magnitude of the estimated bias is quite small, mitigating our concern on this issue. Moreover, because the Census Bureau altered

partial F-statistics on QCT eligibility fall between the first two critical values for both new construction units and new construction low-income units. We keep this in mind for inference, as more conservative, weak-instrument robust confidence intervals would generally lead us to be even less likely to reject the null hypothesis that LIHTC development has no significant effect on homelessness.

[40] As noted earlier, the average census tract in 2000 has a population of 5,241 and a homelessness rate of 0.7 percent, equivalent to 37 homeless and 5,204 non-homeless. If new construction units doubled, this would decrease the homeless count by 1.8 individuals, equivalent to just a 5-percent reduction in homelessness rates. Moreover, despite potential misspecification of constant marginal effects, this magnitude is similar to what we obtain if we instead estimate equation (1) with the dependent variable as the homelessness rate rather than the count, on a sample with all observations. Such estimation results in an IV coefficient on new construction units of -0.007. While not significant, this nevertheless implies that a doubling of new construction units would reduce homelessness rates by 10 percent in the average tract.

its 2000 S-Night methodology to address some of the 1990 shortcomings, λ is likely closer to one in the 2000 data than the 1990 data. Finally, under certain assumptions, the more relevant estimate of λ, at the eligibility threshold, may be closer to one than our current $\hat{\lambda}$ estimate, which reflects the mean in the validation sample.[41]

For comparison to our IV specification, columns (3) and (4) provide estimates from OLS regressions. These specifications show that ignoring the potential endogeneity of LIHTC project placement results in a significantly positive relationship between LIHTC development and homelessness. That said, given the expectedly larger standard errors in IV estimation, the OLS coefficients still fall within most reasonable confidence intervals around our IV estimates. In columns (5)–(8), we focus on the intensive margin effects of LIHTC development on homeless counts. In columns (5) and (6), we examine tracts with at least some homeless individuals. In the homeless count data, there is a mass point at zero, with 33 percent of tracts having no measured homelessness. This large mass indicates that there may be significant nonlinear effects of LIHTC development and other neighborhood characteristics on homelessness that would lead to inconsistent estimation by linear IV. While the estimated coefficients are more negative in these specifications, they are still not statistically significant. This suggests that the linear approximation to the model is fairly reasonable. In columns (7) and (8), we examine the effect of LIHTC development on homelessness for only those tracts with at least some development of the LIHTC measure of interest. Here, the estimated coefficients are smaller in magnitude than those in the main sample specification, and even slightly positive for new construction units. However, these effects remain not statistically significant, in addition to the fact that specifications (5)–(8) all suffer from weak instruments.[42]

Table 4 presents results from county-level analysis. Compared to tract-level analysis,

[41] For instance, if we make the extreme assumption that the decadal increase in homeless counts observed in Table 1 is entirely measurement error, then such error is actually smaller at the threshold than across the overall sample.

[42] In all but two specifications, we also strongly reject the hypothesis that the coefficient on 1990 homelessness equals one, suggesting that adding this variable as a control is indeed preferable to transforming the dependent variable to the decadal change in homelessness.

the estimated impact of LIHTC development on homeless counts at the county level will be more negative if tract-level migration induces an inflow of homeless individuals. Our result in column (3) is consistent with LIHTC development (and possibly QCT eligibility) attracting the homeless to census tracts within a county. An increase of 100 new construction units is estimated to decrease the homeless count by 457 individuals.[43]

Taken together with our estimate that a 100 unit increase in new construction decreases tract-level homelessness by 18 individuals, this suggests that the mobility responses of the homeless population could be substantial. This implies that the unresponsiveness of homelessness to LIHTC development at the neighborhood level masks an elastic, housing-driven response that is nullified by a similarly elastic but opposing mobility-driven response. In the appendix, we further discuss using our tract and county estimates to decompose LIHTC's neighborhood-level effect on homelessness into a "housing effect" due to changes in housing status and a "composition effect" due to population mobility.

A large housing effect may be possible, especially since some LIHTC units in our sample have three or four bedrooms and may thus house several individuals. In analysis similar to our first stage, we examine how QCT eligibility affects the size of units developed, finding significant increases in two-, three-, and four-bedroom units, but not in one-bedroom or efficiency units.[44] There are also several reasons why a large mobility response may be plausible. First, the homeless whose situation is not chronic may be a particularly price-responsive and mobile subset of the population, especially for within-county moves across census tracts. Second, the degree of mobility partly reflects views by those migrating on

[43]The estimate in column (4) of Table 4 for new construction low-income units is similarly negative, albeit smaller in magnitude. However, although this coefficient is statistically significant, the estimation suffers from weak instruments, and so we disregard this result. In the case where county-level estimation does not fully purge LIHTC-driven composition effects, in results not shown, we also examine MSA-level estimation. IV estimation of LIHTC's effect on homelessness at the MSA level is very weak and, thus, these results are unreliable.

[44]Ideally, we would also examine information on the average number of previously homeless people and previously housed tenants in LIHTC units of varying sizes. This would help to provide a rough sense of the plausibility of our estimated housing effect. However, although HUD is collecting new data on LIHTC tenants, prior housing experience is not among the characteristics being surveyed. A second-best alternative might be to use information on the average number of residents in LIHTC units targeted and not targeted to the homeless. Such data, however, are not available.

the substitutability of origin and destination areas.[45] Given our RD design, high-LIHTC-activity and low-LIHTC-activity neighborhoods at the eligibility threshold are extremely close substitutes in terms of area poverty. Lastly, mobility responses to place-based programs can be affected by program features (for example, Kline and Moretti (2014)). Because the LIHTC program does not generally place restrictions on the previous location of new tenants, we might anticipate a larger mobility response than in other place-based programs where such restrictions or incentives exist.[46]

5 Extensions

5.1 Housing Quality of the Housed

In Section 4.2, we examined the role of homeless mobility in the interpretation of tract-level results. However, there are other factors which could also contribute to the negligible neighborhood-level effect of LIHTC development on homelessness. For instance, LIHTC-funded units may not be allocated to those who are on the margin of homelessness but rather to the moderately poor who are already housed. The rent ceiling on subsidized units is relatively high, at 18 percent of AMI, and tenant income limits are set at fairly high levels with only some incentive to obtain tenants with lower levels of income. While policymakers have long been concerned that the LIHTC program serves only the moderately poor,[47] recent work examining the tenants of LIHTC units finds evidence that a substantial portion of LIHTC units are being allocated to those below the poverty line (Horn and

[45]Busso, Gregory, and Kline (2013) interpret the lack of household migration found in their study as reflecting worker beliefs that Empowerment Zones are poor substitutes for residence in neighborhoods outside of such zones.

[46]For instance, the Empowerment Zone program offered firms wage credits if they employed local residents (Kline and Moretti 2014).

[47]For instance, to encourage the provision of LIHTC-funded units to lower-income households, the Administration's Budget proposals over the last three years have included an option for projects to select income requirements regarding a maximum average tenant income.

O'Regan 2013).[48] Nevertheless, these poor households may not be those at the margin of homelessness.

To examine this allocation mechanism, we consider the impact of increased LIHTC activity on the housed population in moderately poor neighborhoods. While we are unable to measure the quality of housing directly, several measures available in the census allow us to infer the quality of housing available to households within a neighborhood. We focus on the possibility that LIHTC development may provide access to higher-quality housing in moderately poor areas.[49] Table 5 examines the impact of LIHTC development on various measures of housing quality of the housed population. The results are suggestive evidence that LIHTC may improve housing quality. For instance, an increase in LIHTC-funded new construction units increases the mean number of rooms per person in units and reduces the median age of structures in the neighborhood. However, neither effect differs significantly from zero. LIHTC development also decreases the share of miscellaneous and one-unit housing structures in a neighborhood. While this may indicate individuals transitioning to higher-quality housing, these effects are likewise not statistically different from zero.[50]

We observe a significant effect of LIHTC development only on the local share of housing structures that are three-to-four units large. Such a result may indicate an increase in housing quality if there are economies of scale in the provision of shared amenities. Meanwhile, the absence of other significant effects of LIHTC activity on housing quality may be due to the data constraining our analysis to the entire housed population in an area rather than just poorer households, who are most likely to be affected.

To further understand our findings, it would be helpful to also know how local rental

[48] Horn and O'Regan (2013) find little evidence that LIHTC program participants are bunched along income limits, as only 20 percent of tenants have incomes at or above 50 percent of AMI.

[49] Alternatively, LIHTC may allow housed individuals to obtain access to equal-quality housing at a lower cost. LIHTC tenants may use such a decrease in rental payments to increase their savings or non-housing consumption.

[50] Miscellaneous structures refers to mobile homes, boats, RVs, vans, and other assorted categories. One-unit structures, if "detached," have open spaces on all four sides or else are joined to only sheds or garages, while if "attached," are joined to another house or building by a dividing wall that goes from ground to roof (Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek 2010). Thus, if these small structures are lower quality, LIHTC might allow individuals to move to higher-quality housing.

prices are changing, if at all, in response to LIHTC development. Such development, if it lowers neighborhood rents through an increase in available low-income housing, could affect the homeless population, the housed population, or both. Ideally, we could test this hypothesis by examining the relationship between LIHTC units and rental prices for the very low end of the rental distribution. However, such information is only available in our data for particular points in the rental distribution, namely the 25th, 50th, and 75th percentiles. When we estimate these regressions, the IV relationship between the number of new construction LIHTC units and the rental prices for each of these percentiles is statistically zero. Nevertheless, we remain unable to conclude that these results indicate a null effect of LIHTC on the full distribution of rental prices.

5.2 External Housing Supply Shocks

In addition to potential effects on the housed population, there may be market spillovers besides the mobility of the homeless that also contribute to LIHTC's lack of an effect on tract-level homelessness. For instance, when a LIHTC unit is created, its new residents may come from a low-income housing unit of a neighboring tract, thus creating a housing vacancy in that neighboring area.[51] Alternatively, a developer's decision to construct new LIHTC housing in a local area may affect developments in neighboring areas. Lastly, LIHTC development in a tract may cause migration between neighborhoods, thus changing both the local area composition (as discussed earlier) and the composition of neighborhoods experiencing no LIHTC development.

To allow for this potential spillover effect of housing supply shocks, we adjust estimating

[51] More broadly, it may be that occupants of new LIHTC housing vacate units within the same area. However, depending on how such a vacancy then filters through the population (for example, Rosenthal (2014)), it might ultimately generate available housing externally in another neighborhood. In contrast, it could be that occupying LIHTC units induces local residents to occupy additional units across neighborhoods, thus reducing housing vacancies in neighboring areas.

equation (1) to incorporate the installation of "external" LIHTC units, $\tilde{L}$:

$$H_i = \beta_0 + \beta_1 L_i + \beta_2 \tilde{L}_i + \mathbf{X}_i' \theta + \varepsilon_i, \tag{4}$$

where $\tilde{L}$ represents LIHTC development external to neighborhood i but within a county. If $\beta_2 \neq 0$, then $\hat{\beta}_{1,IV\_tract}$ is consistently estimated only if LIHTC development across neighborhoods is uncorrelated.

Table 6 provides results from IV estimation of equation (4). We use the number of external tracts in a county that are QCT-eligible to instrument for external LIHTC development. Due to collinearity issues, we include state fixed effects rather than MSA fixed effects as in Table 3. Columns (3) and (4) show that, despite such a change in fixed effects, coefficients remain very similar to the corresponding estimates in columns (3) and (4) of Table 3, although IV estimation is slightly weaker here. With the inclusion of external LIHTC development in columns (1) and (2), we find a negative and statistically significant, albeit small, effect of external development on local area homeless counts.[52] For instance, an increase of 100 external new construction units, 10 times the number in the average tract, is estimated to decrease the local homeless count by 0.39 individuals. Meanwhile, the effect of internal LIHTC development on homeless counts remains similar to non-spillover analysis, albeit somewhat more negative, and is roughly 50 times larger than the external effect. This suggests that there is only a modest negative correlation of LIHTC development across neighborhoods within a county, resulting in little, if any, bias from the omission of external LIHTC development in earlier estimation. In the appendix, we further describe combining the tract-level estimates here with previous county-level estimation to separately identify internal and external housing and composition effects.

[52]Given two endogenous variables being instrumented for instead of one, we use the F-statistic form of the Kleibergen and Paap (2006) rk statistic to evaluate the strength of IV estimation. The Stock and Yogo (2005) critical values for the maximal actual size of a 5-percent Wald test of $\hat{\gamma}_1 = \hat{\gamma}_2 = 0$ are 7.03, 4.58, and 3.95 for maximal test sizes of 10, 15, and 20 percent, respectively. The rk statistic on the QCT instruments exceeds the first critical value for both new construction units and new construction low-income units. Thus, we observe that spillover IV estimation is stronger than its non-spillover counterpart.

5.3 A Model of Housing Supply and Demand

In the appendix (Section A.2), we develop a supply and demand model of low-income housing to further characterize the underlying mechanisms driving the housing effect channel on homelessness. We model the supply of low-income housing as comprising both LIHTC-funded projects and other developments that are targeted towards low-income households. On the supply side, the two parameters of interest are the degree of crowd-out between LIHTC projects and other low-income housing developments, and the extent to which housing developments spill over across neighborhoods. How LIHTC-driven movements in low-income housing supply translate into changes in local homeless counts depends on several factors. In particular, the two parameters of interest here are the price elasticity of demand for low-income housing by the homeless and the proportion of the homeless demanding LIHTC housing who are allocated units.[53] We parameterize the model and use it to gain deeper insight into the estimated housing effect of LIHTC on homelessness.

First, we generate an estimate of the maximal potential housing effect of LIHTC development on homeless counts. For each structural parameter, we assume an estimate that would push the potential effect upwards. We show that under these most generous circumstances, the potential impact of 100 newly constructed LIHTC units is a 2,550-person reduction in the homeless count. Our large estimated internal housing market effect accounts for approximately 21 percent of this maximal potential effect.[54] Evaluated at the 2000 population and LIHTC development levels of the average census tract, our internal housing effect estimate implies that a 10-percent increase in LIHTC local new construction would cause a reduction in the neighborhood homelessness rate of 0.10 percentage points. This is a 14-percent reduc-

[53]The model does not discuss housing quality. However, if some or all LIHTC housing is of high quality, then there will be demand for LIHTC housing by high-income, non-homeless individuals. Given rental limits, this likely creates excess demand for LIHTC housing, which then enters our model via the proportion of the homeless with access to low-income housing. Alternatively, one could assume that high-quality housing must filter down to the homeless as low-quality housing before it is accessible (Rosenthal 2014). Both approaches allow for a less than one-for-one relationship between high-quality LIHTC housing constructed and low-income housing accessible to the homeless.

[54]We focus on the internal housing effect because, as the appendix shows, the external housing effect is simply a scaled version of the internal effect.

tion in the rate, equivalent to a -1.4 elasticity of homelessness rates with respect to LIHTC development.

We next derive the implied local demand elasticity for housing by the homeless based on the estimated internal housing effect. The more the homeless have access to newly constructed LIHTC units, the more inelastic demand for low-income housing by the homeless must be to rationalize a given housing effect. Across different assumptions regarding access and crowd-out, we typically find price-sensitive local housing demand by the homeless with elasticities as large as -1.66. In contrast, not accounting for possible composition and external effects in estimation results in potentially biased, price-insensitive elasticities ranging from -0.02 to -0.04. Compared with other studies focusing on the non-homeless population (for example, Hanushek and Quigley (1980)), the housing demand elasticities in our study could be somewhat larger because there may be group-specific differences between the homeless and the non-homeless in relevant demand factors. Moreover, because we estimate tract-level housing demand, mobility of the homeless across neighborhoods contributes to such demand being more elastic.

Third, we find evidence of modest low-income housing development spillovers across neighborhoods within a county. A 10-unit increase in neighboring low-income housing is associated with a decrease in local low-income housing of 1.4 units. This negative relationship in low-income housing across neighborhoods may arise from the locational preferences of developers, residents, or both.

Lastly, we find heterogeneous internal housing effects of LIHTC on homelessness. We show that compared with other parameters, the allocation mechanism for housing units has the largest theorized impact on the size of the internal housing effect.

6 Conclusion

In this paper, we find that while the LIHTC program increases the local (tract-level) stock of low-income rental units, there is no evidence that these increases reduce local area homelessness in moderately poor neighborhoods. Our estimated effect of LIHTC development on tract-level homelessness is neither statistically nor economically significant. We find that this negligible effect is not driven by measurement error of the homeless population, effects on the housed population, or spillovers in low-income developments across tracts. Our analysis suggests that increases in low-income housing may attract homeless individuals to areas with greater LIHTC activity. This mobility response of the homeless population may make it difficult to detect a low-income housing effect on homelessness at the local level. Once such mobility across neighborhoods is taken into account via county-level estimation, evidence suggests that LIHTC development does reduce area homelessness. Our study thus reveals that the local housing demand of the homeless may be fairly price sensitive, likely due in part to high mobility across neighborhoods.

These results suggest that the effects on homelessness and possibly other outcomes of local expansions of LIHTC may cross local boundaries. Another important policy implication, stemming from our theoretical model, is that the method of allocating low-income units is a particularly important channel for affecting homelessness. Our empirical analysis of LIHTC's impact on housing quality of the housed provides some additional support for the importance of the way that low-income housing units are allocated. These findings are consistent with proposed policies to encourage income mixing and to target LIHTC housing to those at risk of becoming homeless or those who already are homeless (United States Interagency Council on Homelessness 2010). Further examination of LIHTC unit allocation, including more extensive effects on the already-housed, would be of interest and increasingly feasible with the future availability of LIHTC participant data.

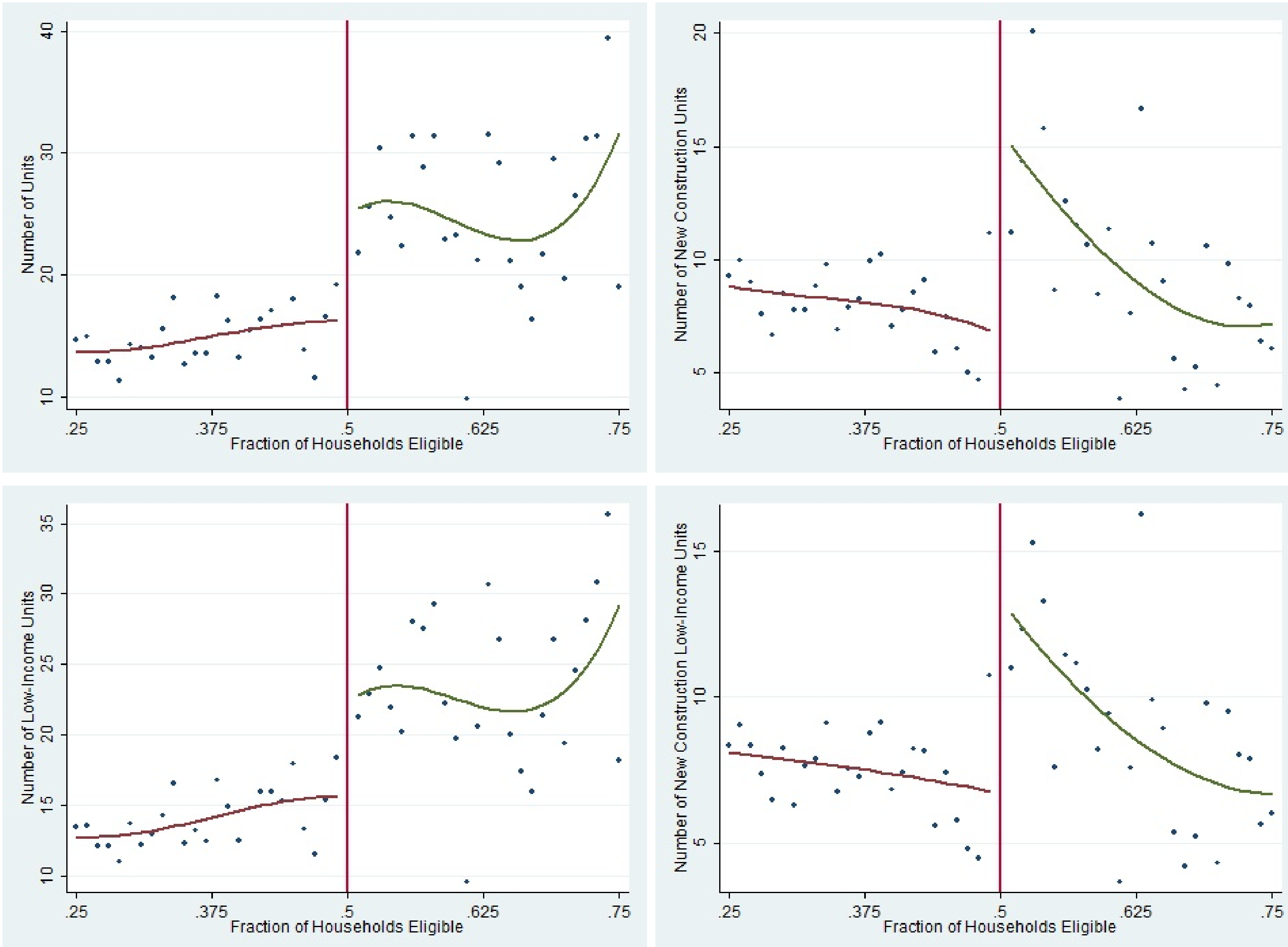

Figure 1: LIHTC Development at the QCT Eligibility Threshold
Source: U.S. Decennial Census, HUD LIHTC Database, and authors' calculations.

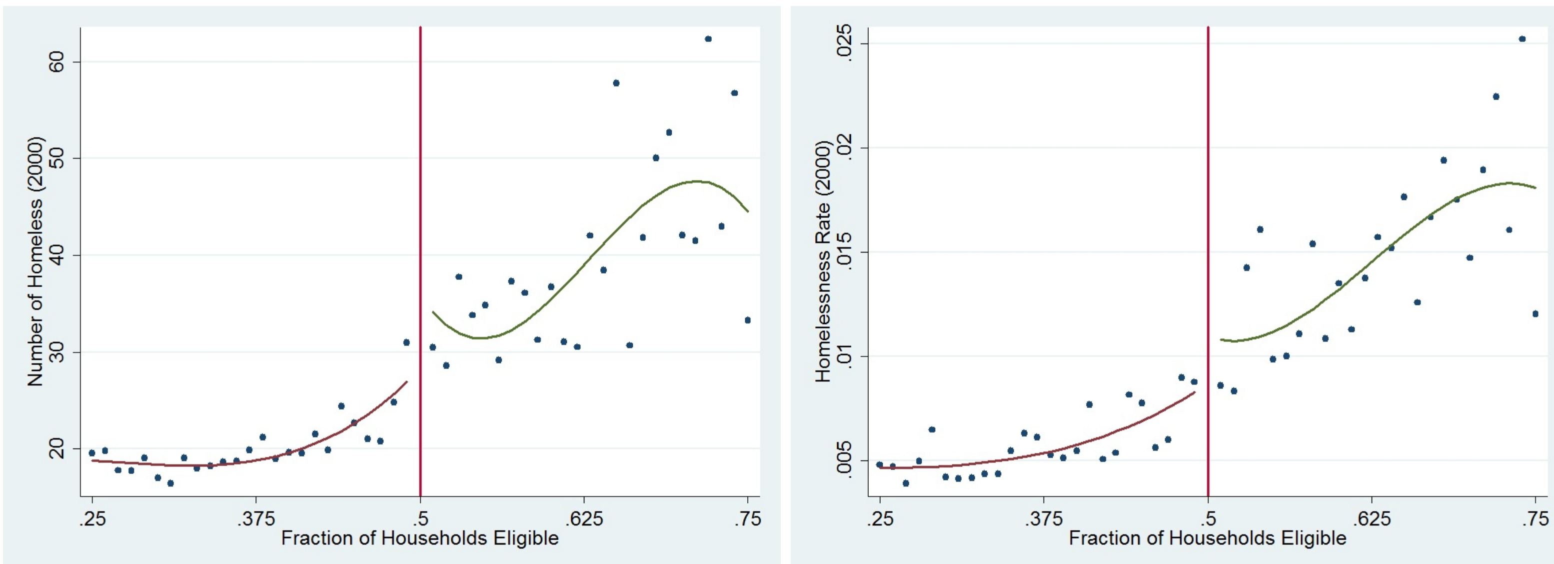

Figure 2: Homelessness at the QCT Eligibility Threshold
Source: U.S. Decennial Census, HUD LIHTC Database, and authors' calculations.

Table 1: Descriptive Statistics of Census Tracts

	Percent of housholds eligible for LIHTC								
	0-25%	25-40%	40-45%	45-50%	50-55%	55-60%	60-75%	75-100%	RD Coeff
Homeless count in 2000	16.59	18.59	20.80	23.92	28.77	33.76	42.52	67.42	-0.92
Homeless count in 1990	1.36	1.98	4.43	6.22	8.29	12.77	17.66	33.53	-0.43
Household median income ($)	43019	27168	21850	19809	18451	16910	13506	8769	-210.8*
Population	4263	4044	3866	3754	3835	3670	3325	2595	125.8*
Household average size	2.68	2.58	2.61	2.66	2.70	2.79	2.82	2.67	0.002
Share black	0.06	0.11	0.21	0.29	0.36	0.44	0.54	0.66	0.01
Share Hispanic	0.04	0.06	0.11	0.14	0.17	0.20	0.22	0.14	-0.001
Share female	0.51	0.52	0.52	0.52	0.52	0.52	0.52	0.53	-0.001
Share married	0.48	0.44	0.38	0.34	0.30	0.27	0.23	0.15	-0.004
Share age 16-24	0.12	0.13	0.14	0.15	0.17	0.17	0.17	0.18	0.01**
Share with less than HS degree	0.12	0.21	0.25	0.27	0.28	0.30	0.33	0.35	-0.01*
Share with HS degree	0.21	0.25	0.23	0.22	0.21	0.19	0.18	0.17	0.01**
Unemployment rate	0.04	0.06	0.09	0.11	0.12	0.13	0.17	0.25	-0.01***
Poverty rate	0.02	0.04	0.05	0.06	0.07	0.08	0.09	0.14	-0.001
Median rent ($)	590	409	377	371	380	374	344	265	-1.06
Rental vacancy rate	0.06	0.07	0.08	0.08	0.09	0.09	0.09	0.10	0.003
LIHTC development									
Units (00s)	0.16	0.14	0.15	0.16	0.26	0.27	0.24	0.35	0.10***
Low-income (LI) units (00s)	0.14	0.13	0.15	0.15	0.24	0.25	0.23	0.33	0.08***
New construction units (00s)	0.12	0.08	0.08	0.07	0.15	0.10	0.08	0.10	0.07***
New construction LI units (00s)	0.11	0.08	0.07	0.07	0.13	0.10	0.08	0.09	0.06***
Observations	10036	12272	2331	1639	1137	953	1932	633	

Notes: Authors' calculations based on data from the U.S. Decennial Censuses and HUD. All census variables are from the 1990 Census except for the 2000 homeless count. LIHTC development is determined by the presence of any LIHTC activity in a tract according to the LIHTC database. The RD coefficient is the estimated discontinuity of the variable listed at the QCT threshold, conditional on a cubic of the running variable and MSA fixed effects. Only tracts with 25-75 percent of eligible households are used to compute these RD coefficients.

Table 2: The Impact of QCT Eligibility on LIHTC Development (OLS)

	Dependent variables				
	All Development		New Construction (NC)		
	Units (00s)	LI units (00s)	Units (00s)	LI units (00s)	Obs
(1) Baseline specification	0.091***	0.072***	0.064***	0.051***	20,264
	(0.031)	(0.027)	(0.019)	(0.017)	
F-stat on QCT = 0	8.42	7.24	11.20	9.22	
Tracts with alternative eligible fraction restrictions					
(2) All observations	0.044	0.030	0.046***	0.036***	30,933
	(0.027)	(0.023)	(0.015)	(0.013)	
(3) Between 0.40-0.60	0.080**	0.062*	0.067***	0.053***	6,060
	(0.039)	(0.035)	(0.022)	(0.020)	
(4) Between 0.45-0.55	0.093**	0.077*	0.060**	0.048**	2,776
	(0.044)	(0.041)	(0.025)	(0.022)	
Placebo tests					
(5) Eligible fraction ≥ 0.3	0.016	0.010	0.008	0.003	20,264
	(0.019)	(0.017)	(0.013)	(0.012)	
(6) Eligible fraction ≥ 0.4	-0.023	-0.015	-0.026*	-0.020	20,264
	(0.020)	(0.019)	(0.015)	(0.013)	
(7) Eligible fraction ≥ 0.6	-0.094***	-0.084***	-0.026	-0.020	20,264
	(0.033)	(0.031)	(0.021)	(0.020)	
(8) Eligible fraction ≥ 0.7	0.038	0.037	0.017	0.014	20,264
	(0.052)	(0.049)	(0.026)	(0.026)	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Authors' calculations based on data from the U.S. Decennial Census and HUD (LIHTC Database and QCT eligibility). All specifications include tract-level controls for the 1990 number of homeless, log of household median income, log of total population, population share black, population share Hispanic, population share female, population share married not separated, population share aged 16-24, population share with less than a high school degree, population share with a high school degree, unemployment rate, poverty rate, log of median rent, rental vacancy rate, and MSA fixed effects. Additionally, most specifications include a third-degree polynomial of the running variable. When we restrict our sample to tracts with the eligible fraction of households between 0.4 and 0.6, we replace the third-degree polynomial of the running variable with a linear function of the running variable. When we restrict our sample to tracts with the eligible fraction of households between 0.45 and 0.55, we do not include the running variable. Standard errors clustered at the MSA level are in parentheses.

Table 3: The Impact of LIHTC on Homelessness

Dependent variable: 2000 Number of Homeless

	IV, Main Sample		OLS		IV, H > 0		IV, L > 0	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NC units (00s)	-18.32		3.89*		-46.65		0.23	
	(38.00)		(2.12)		(59.59)		(53.66)	
NC LI units (00s)		-23.10		4.04*		-61.03		-1.90
		(48.29)		(2.16)		(80.15)		(84.68)
1990 No. homeless	0.62***	0.62***	0.62***	0.62***	0.57***	0.57***	0.94***	0.94***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.13)	(0.14)
F-stat on 1990 H = 1	28.22	29.03	31.54	31.22	37.20	39.20	0.23	0.18
F-stat on QCT = 0	11.20	9.22			7.78	5.38	1.97	1.41
Observations	20,264	20,264	20,264	20,264	11,757	11,757	2,333	2,325
R^2			0.25	0.25				

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Authors' calculations based on data from the U.S. Decennial Censuses and HUD (LIHTC Database and QCT eligibility). The instrument for LIHTC development in IV specifications is QCT eligibility. All specifications include tract-level controls for the 1990 number of homeless, log of household median income, log of total population, population share black, population share Hispanic, population share female, population share married not separated, population share aged 16-24, population share with less than a high school degree, population share with a high school degree, unemployment rate, poverty rate, log of median rent, rental vacancy rate, and MSA fixed effects. IV specifications also include a third-degree polynomial of the running variable. Standard errors clustered at the MSA level are in parentheses.

Table 4: The Impact of LIHTC on Homelessness, County-level

Dependent variable: 2000 Number of Homeless

	WLS		IV	
	(1)	(2)	(3)	(4)
NC units (00s)	-89.79**		-457.26***	
	(37.43)		(134.47)	
NC LI units (00s)		-5.11		-392.25*
		(25.25)		(218.01)
Homelessness rate, 1990	1.21***	1.04***	1.97***	1.25***
	(0.09)	(0.07)	(0.27)	(0.15)
F-stat on QCT Tracts=0			11.60	0.869
Observations	2,102	2,102	2,102	2,102
R^2	0.99	0.99		

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Authors' calculations based on data from the U.S. Decennial Censuses and HUD (LIHTC Database and QCT eligibility). The weights in WLS and IV specifications are the county-level 1990 population. The instrument for LIHTC development in IV specifications is the number of QCT-eligible tracts in a county. All specifications include county-level controls for the 1990 number of homeless, log of household median income, log of total population, log of tracts in county and its quadratic, population share black and higher-order terms, population share Hispanic and higher-order terms, population share female, population share married not separated, population share aged 16-24, population share with less than a high school degree and higher-order terms, population share with a high school degree, unemployment rate and higher-order terms, poverty rate and higher-order terms, log of median rent and higher-order terms, rental vacancy rate and higher-order terms, and MSA fixed effects. IV specifications also include a county-level analog of the third-degree polynomial of the running variable, tract QCT eligibility. Standard errors clustered at the MSA level are in parentheses.

Table 5: The Impact of LIHTC Development on the Housed (IV)

Dependent variables: Measures of Housing Quality of the Housed Population (2000)

	Hhld		Year	Share of All Structures: No. of Units				
	Size	Rooms	Built	Misc	1	2	3-4	5-9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NC units (00s)	0.015	0.050	3.624	-0.012	-0.048	0.023	0.048*	-0.023
	(0.160)	(0.074)	(3.716)	(0.033)	(0.049)	(0.031)	(0.029)	(0.028)
Observations	20,145	20,153	20,137	20,153	20,153	20,153	20,153	20,153

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Authors' calculations based on data from the U.S. Decennial Censuses and HUD (LIHTC Database and QCT eligibility). The instrument for LIHTC development in all specifications is QCT eligibility. The following are the dependent variables in each specification, all measured in the 2000 Census: (1) "Hhld Size" is the mean number of persons per household; (2) "Rooms" is the mean number of persons per room in units; (3) "Year Built" is the median year that structures in the tract were built; and specifications (4) to (8) each refer to the share of all housing structures in the given category, arranged by number of units in the structure. Specification (4), "Misc" refers to mobile homes, boats, RVs, vans, and other miscellaneous housing categories. All specifications include a third-degree polynomial of the running variable as well as tract-level controls for the relevant dependent variable in 1990, log of household median income, log of total population, population share black, population share Hispanic, population share female, population share married not separated, population share aged 16-24, population share with less than a high school degree, population share with a high school degree, unemployment rate, poverty rate, log of median rent, rental vacancy rate, and MSA fixed effects. Standard errors clustered at the MSA level are in parentheses.

Table 6: Spillovers in the Impact of LIHTC on Homelessness (IV)

Dependent variable: 2000 Number of Homeless

	(1)	(2)	(3)	(4)
NC units internal (00s)	-17.90		-16.29	
	(40.15)		(39.77)	
NC units external (00s)	-0.39**			
	(0.17)			
NC LI units internal (00s)		-25.07		-21.09
		(53.29)		(51.76)
NC LI units external (00s)		-0.44**		
		(0.22)		
1990 No. homeless	0.62***	0.62***	0.62***	0.62***
	(0.07)	(0.07)	(0.07)	(0.07)
F-stat on 1990 H = 1	29.57	29.82	27.69	28.34
rk-stat on QCT vars	8.249	7.226		
F-stat on QCT = 0			9.446	7.360
Observations	20,264	20,264	20,264	20,264

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Authors' calculations based on data from the U.S. Decennial Censuses and HUD (LIHTC Database and QCT eligibility). Internal units, as before, refer to LIHTC development within a tract, while external units refer to LIHTC development outside of a tract but within its county. The instrument for internal LIHTC development in IV specifications is the QCT eligibility of a tract, while the instrument for external LIHTC development is the number of QCT-eligible external tracts in a county. All specifications include a third-degree polynomial of the running variable, as well as other tract-level controls for the 1990 number of homeless, log of household median income, log of total population, population share black, population share Hispanic, population share female, population share married not separated, population share aged 16-24, population share with less than a high school degree, population share with a high school degree, unemployment rate, poverty rate, log of median rent, rental vacancy rate, and state fixed effects. Standard errors clustered at the MSA level are in parentheses. The rk-stat refers to the F-statistic form of the Kleibergen and Paap (2006) rk statistic. The null hypothesis is that the test matrix of minimal canonical correlations between the endogenous variables and the instruments is just below full rank (that is, weak), with the alternative being full rank.

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A Appendix

A.1 Identifying Housing and Composition Effects

We show how our estimates of the impact of LIHTC development on homelessness at the tract level and county level can be combined to inform the composition and housing effects of the homeless population at the tract level in principle. If LIHTC development causes shifts in the homeless population, these tract-level estimates capture changes in the homeless count through both a change in housing and a change in the population composition of a tract. We can rewrite the probability limit of $\hat{\beta}_{1,IV\_tract}$ as:

$$\text{plim } \hat{\beta}_{1,IV\_tract} = \frac{\partial H}{\partial L} = \underbrace{\Big(\frac{\partial H}{\partial COMP} \times \frac{\partial COMP}{\partial L}\Big)}_{\text{composition effect}} + \underbrace{\Big(\frac{\partial H}{\partial LIH} \times \frac{\partial LIH}{\partial L}\Big)}_{\text{housing effect}}, \quad (5)$$

where, recall, L is nearby LIHTC units and H is the local area number of homeless, while $COMP$ captures the area composition of the homeless and non-homeless populations and LIH is the total supply of low-income housing.[55] If the composition effect is purged in our county-level estimates, then we can interpret our county-level estimate as the impact of LIHTC on homeless counts due to a change in the housing status of the homeless (that is, plim $\hat{\beta}_{1,IV\_county} = \frac{\partial H}{\partial LIH} \times \frac{\partial LIH}{\partial L}$).

If we take the point estimates from our empirical analysis of new construction units at face value (that is, $\hat{\beta}_{1,IV\_tract} = -18.32$ and $\hat{\beta}_{1,IV\_county} = -457.26$), this formulation implies that $\frac{\partial H}{\partial L} \approx -18.32 = (438.94) + (-457.26)$. Thus, for every 100 newly constructed LIHTC units, the induced tract-level migration of the homeless (and possibly of the non-homeless) increases the local homeless count by about 439 individuals, while changes in the housing status of the homeless decrease the local homeless count by about 457 individuals.[56]

In our estimation sample in 2000, the average census tract has 10 new construction LIHTC units, a population of 5,241, and a homelessness rate of 0.7 percent, equivalent to approximately 37 homeless and 5,204 non-homeless individuals. New construction units increasing by 10 percent in the average tract would cause a composition effect equivalent to 4.39 homeless individuals migrating to a tract due to new LIHTC development. Meanwhile, this same 10-percent increase in LIHTC new construction would cause a housing effect equivalent to 4.57 homeless individuals becoming housed due to new LIHTC development. In the absence of any composition effects, this would lead to a new homelessness rate of 0.62 percent, a reduction of 0.08 percentage points or 11 percent. This is equivalent to an elasticity of homelessness rates with respect to LIHTC development of -1.1, as opposed to the -0.05 elasticity implied by our baseline results from Section 4.

Next, we allow for the external housing supply shocks that we estimate in section 5. We

[55] As discussed, homeless mobility is also a concern, since consistent tract-level IV estimation assumes that, for otherwise similar tracts, the homeless do not use QCT eligibility when choosing where to locate.

[56] The comparable magnitudes of the composition and housing effects are sensible if migration decisions by the homeless are driven by uncertain expectations over the amount of housing likely to be available. Homeless individuals who relocate but do not acquire an affordable housing unit may nevertheless stay because of local services associated with increased low-income housing or the expectation of additional LIHTC development in the future.

can now combine our tract-level and county-level coefficients to approximate the magnitudes of the internal and external composition and housing effects at the tract level. We rewrite the parameters of interest in equation 4 of our spillover analysis to allow for population mobility and housing effects. Specifically:

$$\text{plim } \hat{\beta}_{1,IV\_tract} = \underbrace{\Big(\frac{\partial H}{\partial COMP} \times \frac{\partial COMP}{\partial L}\Big)}_{\text{internal composition effect}} + \underbrace{\Big(\frac{\partial H}{\partial LIH} \times \frac{\partial LIH}{\partial L}\Big)}_{\text{internal housing effect}}, \tag{6}$$

$$\text{plim } \hat{\beta}_{2,IV\_tract} = \underbrace{\Big(\frac{\partial H}{\partial COMP} \times \frac{\partial COMP}{\partial \tilde{L}}\Big)}_{\text{external composition effect}} + \underbrace{\Big(\frac{\partial H}{\partial LIH} \times \frac{\partial LIH}{\partial \tilde{L}}\Big)}_{\text{external housing effect}}. \tag{7}$$

Lastly, assuming that LIHTC-driven migration occurs only between tracts within a county and not between counties, plim $\hat{\beta}_{1,IV\_county}$ mentioned earlier is equal to the sum of the internal and external housing effects.

To separately identify the internal and external housing effects, we impose an identifying assumption regarding composition effects. Specifically, we assume that the migration flows of the homeless that drive the composition effects are random. Thus, LIHTC-driven outflows from a tract become evenly dispersed inflows into all other tracts within the county.[57] More specifically:

$$\text{external composition effect} = -\Big(\frac{1}{N_{county} - 1}\Big)\Big(\text{internal composition effect}\Big), \tag{8}$$

where N_{county} is the number of tracts in a given county and can be proxied with $\overline{N_{county}}$, the average number of tracts in counties.[58] The total composition effect, which is the sum of the internal and external effects, is $\hat{\beta}_{1,IV\_tract} + \hat{\beta}_{2,IV\_tract} - \hat{\beta}_{1,IV\_county}$. Combined with equation (8), we can identify an estimate of the internal composition effect as:

$$\text{internal } \widehat{\text{composition}} \text{ effect} = \Big(\frac{\overline{N_{county}} - 1}{\overline{N_{county}} - 2}\Big)\Big(\hat{\beta}_{1,IV\_tract} + \hat{\beta}_{2,IV\_tract} - \hat{\beta}_{1,IV\_county}\Big). \tag{9}$$

As equation (9) suggests, there need to be on average more than two tracts per county in

[57]In a two-tract county, this would imply an external composition effect that is of opposite sign and equal magnitude to the internal composition effect. Meanwhile, in a three-tract county, this would result in an external composition effect that is again of opposite sign but one-half the magnitude of the internal composition effect.

[58]Formally, we can rewrite the external composition effect as $\frac{\partial H}{\partial COMP} \times \frac{\partial \tilde{COMP}}{\partial \tilde{L}} \times \frac{\partial COMP}{\partial \tilde{COMP}}$. If the effect of increased LIHTC housing on neighborhood composition does not differ by neighborhood, then $\frac{\partial COMP}{\partial L} = \frac{\partial \tilde{COMP}}{\partial \tilde{L}}$. Thus, the internal and external composition effects differ only by $\frac{\partial COMP}{\partial \tilde{COMP}}$, the spillover effect of a change in external neighborhood composition on internal neighborhood composition. For tract i, let $d\tilde{COMP}_i = -\sum_j dCOMP_j$, where j indexes all other tracts in the county. The simplifying assumption of random migration flows means that $dCOMP_j = dCOMP_k \equiv dCOMP \; \forall j \neq k$. This implies for a two-tract county, $d\tilde{COMP} = -dCOMP$, so $-1 = \frac{dCOMP}{d\tilde{COMP}}$. For a three-tract county, $d\tilde{COMP} = -(dCOMP_1 + dCOMP_2) = -2dCOMP$, so $-\frac{1}{2} = \frac{dCOMP}{d\tilde{COMP}}$. In general, for a J-tract county, $-\frac{1}{(J-1)} = \frac{dCOMP}{d\tilde{COMP}}$. Equation (8) follows.

order to identify the internal composition effect. In turn, combining equations (8) and (9), the external composition effect is estimated as:

$$\widehat{\text{external composition effect}} = -\Big(\frac{1}{\overline{N_{county}} - 1}\Big)\Big(\widehat{\text{internal composition effect}}\Big). \tag{10}$$

Our estimates of the internal and external composition effects, combined with equations (6) and (7), allow us to separately identify the internal and external housing effects:

$$\widehat{\text{internal housing effect}} = \hat{\beta}_{1,IV\_tract} - \widehat{\text{internal composition effect}}, \tag{11}$$

$$\widehat{\text{external housing effect}} = \hat{\beta}_{2,IV\_tract} - \widehat{\text{external composition effect}}. \tag{12}$$

We find the internal composition effect to be 514.23, the external composition effect to be -75.26, the internal housing effect to be -532.13, and the external housing effect to be 74.87, with all magnitudes corresponding to the impact on homeless counts from an increase of 100 new construction units. The positive external housing effect arises from the negative association between neighboring and local low-income housing mentioned earlier. Due to this negative relationship, we expect that an increase in external housing increases local homelessness due to the decreased availability of local housing.[59]

A.2 A Supply-Demand Model of Low-Income Housing

To understand the mechanisms that determine the impact of LIHTC development on homelessness, we develop a supply and demand model of low-income housing. Variables are as defined in the main text.[60] There are both direct effects of LIHTC development within a given neighborhood and spillover effects between neighborhoods. The model developed here formalizes the internal and external housing effects contained in equations (6) and (7). We then parameterize the model to provide estimates of the potential magnitudes of these effects as well as other analysis.

Low-income housing is generally supplied through three channels: (1) LIHTC-funded development (LIH_{LIHTC}), (2) other private-funded development (LIH_{Other}), and (3) public housing (LIH_{Public}), such as HUD's public housing programs. The effect of a within-neighborhood increase in LIHTC housing on the overall local supply of low-income housing is therefore given by:

$$\frac{\partial LIH}{\partial L} = \left(\frac{\partial LIH_{Public}}{\partial L} + \frac{\partial LIH_{Other}}{\partial L} + \frac{\partial LIH_{LIHTC}}{\partial L}\right) \equiv \Big(\underbrace{\delta_{Pub} + \delta_{Oth}}_{\delta} + 1\Big). \tag{13}$$

[59]It is also worth noting that the sum of the internal and external composition effects, 439, and the sum of the internal and external housing effects, -457, are equivalent to the composition and housing effects described by equation 5, estimated without external supply shocks. Thus, the magnitudes of the external effects help to inform the extent of bias in previous estimation of the internal effects. Those prior estimates can thus be reinterpreted as consistent estimates of total effects (that is, internal plus external).

[60]In the model, H represents the local area homelessness, LIH is the local area low-income housing supply, L represents local area LIHTC units, and $\tilde{L}$ represents neighboring LIHTC units.

In equation (13), δ captures how much LIHTC development crowds out other private and public housing developments, and thus determines the sign of $\frac{\partial LIH}{\partial L}$.

The supply of local low-income housing may also be affected by LIHTC development in neighboring areas through spillovers. This relationship is given by $\frac{\partial LIH}{\partial \tilde{L}}$, which can be rewritten as: $\frac{\partial LIH}{\partial L\tilde{I}H} \times \frac{\partial L\tilde{I}H}{\partial \tilde{L}}$. The second term represents the impact that LIHTC development in a neighborhood has on the supply of low-income housing within that neighborhood. We assume that the degree of crowd-out of other sources of low-income housing that occurs in response to LIHTC development is constant across neighborhoods. Thus, this term is equal to $\delta + 1$ as above. The first term represents the spillovers in low-income housing supply across neighborhoods, which we represent by κ. Put together, the impact of external LIHTC development on internal low-income housing is given by:

$$\frac{\partial LIH}{\partial \tilde{L}} = \kappa(\delta + 1). \tag{14}$$

In both the internal and external housing effects of LIHTC on homelessness, $\frac{\partial H}{\partial LIH}$ represents the effect of an increase in the supply of low-income housing on local area homelessness. This effect operates through those on the margin of homelessness becoming housed in low-income housing units. To understand this component, let us first define $LIH^{D,H}$ as the amount of low-income housing demanded by homeless individuals and LIH^{S} as the amount of low-income housing supplied. $LIH^{D,H} = D(P, \xi)$ and $LIH^{S} = S(P, \zeta)$, where P is the price of low-income housing (that is, rent) and ξ and ζ are demand and supply shifters, respectively. In equilibrium, $LIH^{D,H*} = LIH^{S*} = LIH^{H*}$.

The increase in the equilibrium low-income housing stock demanded by the homeless that arises from an exogenous shift in housing supply is as follows:

$$\frac{\partial LIH^{H*}}{\partial \zeta} = \frac{\partial S}{\partial \zeta}\Big(\frac{\eta}{\eta - \phi}\Big), \tag{15}$$

where $\eta = \frac{\partial \ln LIH^{D,H}}{\partial \ln P} \leq 0$ and $\phi = \frac{\partial \ln LIH^{S}}{\partial \ln P} \geq 0$ are, respectively, the price elasticities of low-income housing demand by the homeless and low-income housing supply.[61] We have already defined $\frac{\partial S}{\partial \zeta}$ in the housing effects (equations (13) and (14)). Thus, the only remaining piece that determines $\frac{\partial H}{\partial LIH}$ is $\frac{\eta}{\eta - \phi}$. We write:

$$\frac{\partial H}{\partial LIH} = -\frac{\rho \pi \eta}{\eta - \phi}, \tag{16}$$

where π is the proportion of the homeless demanding LIHTC housing at the given rental price with access to such housing, determined by the allocation behavior of low-income housing owners. Meanwhile, ρ is the number of homeless individuals occupying a low-income housing unit.

These components of local low-income housing supply and demand allow us to rewrite

[61] Taking total differentials yields $dLIH^{D,H} = \frac{\partial D}{\partial P}dP + \frac{\partial D}{\partial \xi}d\xi$ and $dLIH^{S} = \frac{\partial S}{\partial P}dP + \frac{\partial S}{\partial \zeta}d\zeta$, as well as the equilibrium condition $dLIH^{D,H*} = dLIH^{S*} = dLIH^{H*}$. Setting $d\xi = 0$, solving for $\frac{\partial LIH^{H*}}{\partial \zeta}$, and rewriting in terms of elasticities yields equation (15).

the housing impact of internal LIHTC development on homelessness as:

$$\frac{\partial H}{\partial L} = \frac{\partial H}{\partial LIH} \times \frac{\partial LIH}{\partial L} = -\Big(\frac{\rho\pi\eta}{\eta - \phi}\Big)\Big(\delta + 1\Big), \tag{17}$$

and rewrite the housing impact of external LIHTC development on homelessness as:

$$\frac{\partial H}{\partial \tilde{L}} = \frac{\partial H}{\partial LIH} \times \frac{\partial LIH}{\partial \tilde{L}} = -\Big(\frac{\rho\pi\eta}{\eta - \phi}\Big)\Big[\kappa\Big(\delta + 1\Big)\Big]. \tag{18}$$

A.3 Computing the Maximal Potential Effect of LIHTC

To quantify the potential responses of the homeless to the placement of LIHTC units, we parameterize δ, η, and π.[62] Because the internal and external housing effects are identical other than κ, we restrict our attention to the internal effect for this analysis, noting that the implications for the external effect are the same but are scaled by $\kappa \in (-\infty, \infty)$.

To start, we must bound our parameters of interest. Note that $\eta = \frac{\partial \ln LIH^{D,H}}{\partial \ln P} \leq 0$ and $\phi = \frac{\partial \ln LIH^{S}}{\partial \ln P} \geq 0$ results in $\frac{\eta}{\eta - \phi} \in [0, 1]$.[63] We assume that neither crowd-in nor greater than one-for-one crowd-out are possible, which restricts $\delta \in [-1, 0]$ and $(\delta + 1) \in [0, 1]$. Note also that $\pi \in [0, 1]$ and $\rho \geq 0$. Finally, our model allows us to determine a value for $\kappa \in (-\infty, \infty)$, the parameter that represents $\frac{\partial LIH}{\partial \tilde{LIH}}$. We estimate κ with the ratio of external to internal housing effects, (74.9/-532.1) = -0.14.

For an exercise on the *maximum* reasonable internal housing effect of LIHTC on homelessness using the model, we utilize parameter values that push upwards our estimate of the potential impact of LIHTC. For every new unit made available, we assume that the number of homeless that could occupy a unit is 26.7, 10 times the average household size in our sample, because the homeless population may live in more crowded spaces. Because our housing development measures represent every 100 LIHTC units, for this exercise we additionally multiply the number of homeless per unit by 100 units. We assume that the price elasticity of low-income housing supply is 0.3 (one-tenth of the long-run estimate in Topel and Rosen (1988)) and that the price elasticity of homeless low-income housing demand is -6.4, 10 times the long-run estimate in the Hanushek and Quigley (1980) model using data on Pittsburgh. Lastly, we assume that there is no crowd-out and that all the homeless demanding low-income units at equilibrium rental prices have access. Results from this exercise are presented in Section 5.[64]

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[62] The focus on these parameters might be reasonable, for instance, if $d\phi = d\rho = d\kappa = 0$ (for example, these parameters are relatively constant or cannot be changed exogenously).

[63] The sole exception to this is when $\eta = \phi = 0$, in which case $\frac{\eta}{\eta - \phi}$ is indeterminate.

[64] Note that with a feasible but less reasonable change in assumptions to perfectly inelastic low-income housing supply and perfectly elastic low-income housing demand, the maximum effect would be a 2,670-person reduction in the homeless count for every 100 low-income units built, rather than our stated 2,550-person reduction. Thus, the true upper bound of the internal housing effect is determined by the number of homeless per unit, as alluded to in Section 4 and our discussion of first-stage magnitudes.

A.4 Relative Importance of Mechanisms

Our analysis suggests that δ (crowd-out), π (allocation), and η (homeless housing demand) are dimensions of heterogeneity where one could anticipate differential effects of LIHTC development on homelessness. Our earlier parameterization suggests that $T = \frac{\partial H}{\partial L} \leq 0$. To determine the relative importance of each of the mechanisms that we have identified, we take second derivatives to understand the nature of each mechanism's impact on homelessness, given by:

$$\frac{\partial T}{\partial \delta} = -\Big(\frac{\rho\pi\eta}{\eta - \phi}\Big) \leq 0, \tag{19}$$

$$\frac{\partial T}{\partial \pi} = -\Big(\frac{\rho\eta}{\eta - \phi}\Big)\Big(\delta + 1\Big) \leq 0, \tag{20}$$

and

$$\frac{\partial T}{\partial \eta} = -\Big[\Big(\frac{\rho\pi}{\eta - \phi}\Big)\Big(\delta + 1\Big)\Big]\Big[1 - \frac{\eta}{\eta - \phi}\Big] \geq 0. \tag{21}$$

Equation (19) shows that reducing the degree to which LIHTC development crowds out other low-income housing developments (that is, by increasing δ) will result in a (weakly) more negative housing effect of LIHTC on homelessness. Similarly, equations (20) and (21), respectively, imply that increasing the proportion of the homeless with access to LIHTC housing units (by increasing π) or increasing the magnitude of the price elasticity of low-income housing demand by the homeless (by lowering η) results in a (weakly) more negative housing effect of LIHTC on homelessness.

We can compare magnitudes of the marginal effects in equations (19)–(21) to determine each mechanism's importance. In this exercise (available upon request), we use parameter estimates found in the existing literature as a baseline when available.[65] The exercise shows that the LIHTC housing effect is most sensitive to the allocation mechanism, followed by the degree of development crowd-out, and finally the price-elasticity of housing demand by the homeless (that is, $|\frac{\partial T}{\partial \pi}| \geq |\frac{\partial T}{\partial \delta}| \geq |\frac{\partial T}{\partial \eta}|$).[66]

In additional empirical analysis (available upon request), we use proxies for these parameters to examine directly whether the model's hypotheses hold, interacting the proxies with LIHTC development. The results we obtain are generally consistent with the model's predictions, although not statistically significant.[67]

[65] Specifically, $\delta = -0.2$, implying $\delta + 1 = 0.8$ (Baum-Snow and Marion 2009).

[66] However, this is distinct from cost-effectiveness since, for instance, $d\delta$ may be less costly than $d\pi$, and since homeless count reductions would need to be valued.

[67] We use the log of the median rent as the crowd-out proxy, since as the degree of crowd-out increases, we would expect market rents to remain higher, given the smaller increase in housing supply. We use the share of LIHTC units targeted to the homeless to proxy for the share of the homeless with access to LIHTC units. Finally, since mental illness, drug use, and veteran status may be positive, nonprice determinants of homelessness, such individuals should be more price inelastic in their demand for low-income housing. We therefore use the population shares of these groups as our proxy for demand elasticity.