

**Crowd Out Effects of Place-Based Subsidized Rental Housing
New Evidence from the LIHTC Program**

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December 21, 2008

Funding for this project from the John D. and Catherine T. MacArthur Foundation, the Ford Foundation and the Department of Housing and Urban Development is gratefully acknowledged. We thank two anonymous referees, Denise DiPasquale, Gary Engelhardt, Jeffrey Kubik, Edgar Olsen, Erika Poethig, Steve Ross, Michael Stegman, Bruce Weinberg, Johnny Yinger, and seminar participants at the January 2007 AREUEA meetings and Ohio State University for helpful comments. Any remaining errors are ours alone.

Abstract

Since its inception in 1987, the Low-Income Housing Tax Credit (LIHTC) program has ballooned into the largest ever source of subsidized construction of low-income housing in the United States, accounting for one-third of all recent multi-family rental construction. This paper examines the crowd out effects of this increasingly important source of low-moderate income housing. To do so, we apply a geographic approach to the data while also using political variables as instruments to facilitate identification.

For areas up to five miles radius in size, IV estimates indicate that roughly half of LIHTC development is offset by reductions in unsubsidized construction of rental housing. For areas 10-miles radius in size and also county-level assessments, crowd out is nearly 100 percent. We also find that crowd out effects occur primarily in the rental as opposed to owner-occupied sector of the housing market. Overall, while LIHTC development may well affect the location of low-moderate income rental housing opportunities, the impact of the program on the total number of newly developed rental housing units appears small.

Key Words: Crowd Out, Subsidized Housing, LIHTC

JEL Codes: H7, H42, R21, R31

“I rise today to introduce the Affordable Housing Tax Credit Enhancement Act of 2005. ... the bill would double the current LIHTC [annual allocations], which would yield twice the number of affordable units annually. ... Today, the LIHTC program is widely regarded as the nation’s most successful housing production program resulting in the construction and rehabilitation of more than 1.3 million housing units for lower income households. ...”

*Statements Submitted to Congressional Record: May 26, 2005
By Rep. William Jefferson (D-LA)*

1. Introduction

The manner in which housing assistance to the poor is provided remains subject to considerable and even heated debate: should government invest in people through demand side voucher type programs (e.g. Section 8 vouchers) or in places through supply side construction subsidies such as public and Low Income Housing Tax Credit (LIHTC) housing? Against that backdrop, this paper examines the rapidly growing LIHTC program and highlights the extent to which construction of LIHTC housing displaces or crowds out unsubsidized private development of rental housing. Some further context will help to put the LIHTC program in perspective.

Between the late 1930s and the mid-1980s, the federal government built over one million low-income units through the public housing program. During the 1980s, construction of new public housing units ended and was replaced in 1986 by the Low-Income Housing Tax Credit (LIHTC) program. Under different variants of the LIHTC program between 30 to 91 percent of project construction costs are subsidized. Those subsidies are financed by the Federal government in the form of tax credits administered through the Internal Revenue Service (IRS). In each year, Congress sets the total number of credits to be granted nationwide, and allocates those credits across states in proportion to their population. State housing authorities then reallocate credits to developers who agree to adhere to rent ceilings and tenant income limits for at least 15 years.

In Table 1, notice that from 1987 to 2006, roughly 1.6 million LIHTC units were built accounting for roughly one-third of all recent multi-family rental housing constructed. This makes the LIHTC program the largest supply-side housing subsidy program in the nation’s history. Figure 1 further illustrates this point. The figure displays the level of public housing and LIHTC development by decade

over the last 60 years.¹ The recent boom in LIHTC development is evident. Also apparent, in Table 2 note that while the cost of the LIHTC program may appear modest in relation to the housing voucher program, the absolute cost of the LIHTC program is large. In 2006, housing voucher programs cost nearly \$21 billion. In comparison, lost federal tax revenue associated with the LIHTC program totaled \$4.9 billion. That cost, however, is expected to increase sharply in the next few years in response to the 40 percent increase in credits allocated beginning in 2001.² Moreover, as recently as May, 2005, there have been calls in congress to substantially increase the size of the LIHTC program.

It is also worth highlighting that LIHTC development is not exclusively a low-income neighborhood event. As shown in Figure 2a, as of 2000, 16 percent of LIHTC units were located in census tracts in the upper third of their MSA income distribution. Another 28 percent were situated in middle-income communities, with the remaining 56 percent in lower-third income neighborhoods. The extension of LIHTC housing into middle- and higher-income neighborhoods differs markedly from public housing. In Figure 2b, observe that 77 percent of public housing units are in low-income locations with most of the rest in middle-income communities. Although our primary focus in this paper is to consider the extent to which LIHTC development displaces unsubsidized rental housing construction, it is important to recognize that even in the event of full crowd out, the patterns in Figure 2 are suggestive that LIHTC development may affect the location of rental housing opportunities.

To assess the crowd out effects of LIHTC development we combine census tract data from 1990 with information on LIHTC development between 1990 and 2000. Our basic strategy is to run cross-section regressions of private sector housing construction in the 1990s on LIHTC development over the same period, controlling for other drivers of housing starts as articulated in prior literature (e.g. Mayer

¹The public housing data used to create Figure 1 were obtained from analysts at HUD and with assistance from MacArthur and Abt Associates. These data differ from the publicly available series found at www.huduser.org in two ways. First, our data contain the year each “project” was placed-in-service from 1937 to 2000. This allows us to represent new construction of public housing in each decade. Additionally, our data also includes information on public housing demolitions in the 1990’s. The LIHTC data were obtained from HUD at <http://lihtc.huduser.org>.

²Those increases will occur even if current proposals seeking to expand the LIHTC program are not born out. Additional details on the cost of various forms of low-income housing support are provided in a report by the U.S. Congress, Joint Committee on Taxation (2005).

and Somerville, 2000). An alternative approach, emphasized by Murray (1999) in his analysis of aggregate time series of U.S. housing stocks, would be to assess the impact of subsidized housing construction on the total stock of housing. We argue later in the paper that our focus on new development yields closely related results that are more reliable given the largely cross-sectional nature of our data. In particular, we condition all of our models on lagged levels of housing stocks. This helps to control for unobserved local factors that might otherwise bias our estimates. This also causes our dependent variable to reflect the change in housing stocks between 1990 and 2000 regardless of whether the dependent variable is specified as the change in housing stock or as the year-2000 level of housing stock.³ It should also be noted that change in stock over time is equal to new construction net of demolitions. Our data provide direct observations on new construction but demolitions are not reported and can only be inferred. Accordingly, we believe that our data on new construction is more reliable and for that reason we focus our analysis on the impact of LIHTC development on unsubsidized housing starts. Nevertheless, two related empirical challenges remain that play a prominent role in our effort to identify crowd out effects: the degree to which crowd out effects differ with the geographic scope of the analysis, and the possibility that LIHTC development may be endogenous. We consider each of these issues briefly in turn below, with further details to follow later in the paper.

A basic principle of consumer demand is that demand for broader categories of goods tends to be more inelastic than demand for smaller subcategories. The reason is that there are more close substitutes for subcategories of products and services (e.g. a specific type of vehicle versus automobiles). In the present context, demand for low-moderate rental housing in a broad geographic region will be more inelastic as compared to demand for comparable housing in a given community within the broader area: this is because households can readily substitute across local enclaves when making their housing decisions causing housing demand at the neighborhood level to be elastic. We argue later that crowd out

³Note, for example, if we subtract y_{t-1} from both sides of $y_t = b_0 + b_1 y_{t-1} + b_2 x_t$ only the coefficient on the lagged dependent variable is affected while the coefficient on x remains unchanged. In addition, whereas Murray (1999) seeks to analyze the impact of subsidized housing construction on equilibrium stocks of housing, Murray (1983) alternatively focuses on the impact of subsidized housing development on housing starts.

effects increase as demand becomes more inelastic, and as a consequence, crowd out effects will be more pronounced when considering larger geographic areas. For this reason, we estimate our models several times for areas of increasingly large geographic scope (1, 2, ...5, and 10 mile circle areas, as well as county-level regressions). Varying the size of geographic units of analysis allows us to highlight the importance of taking geography into account when assessing the crowd out effects of LIHTC and other location specific programs.

For any given level of geographic analysis, endogenous placement of LIHTC projects could arise for two quite different types of reasons. On the one hand, developers recognize that the potential for capital gains varies with location and this affects the anticipated returns on a LIHTC project. In addition, sharp financial penalties are imposed on LIHTC investors if a project fails to meet federal and state guidelines requiring a minimum share of project units to be leased out to low-income families (Eriksen, 2007).⁴ The risk of incurring such penalties is sensitive to fluctuations in demand for low-moderate income rental housing and is likely to differ across locations. For these reasons and others, it is plausible that developers might seek to locate LIHTC projects in areas perceived to be ripe for future growth. On the other hand, it is also possible that state officials overseeing within-state allocations of LIHTC credits may pressure developers to site projects in hard pressed communities where little development might otherwise be anticipated. Together, these considerations suggest that failure to control for the possible endogenous location of LIHTC projects could bias estimates of LIHTC crowd out effects, although the direction of bias is uncertain, *a priori*.

To control for the endogenous placement of LIHTC units, we instrument for LIHTC development in a two-stage least squares procedure using instruments motivated by the political process that governs the allocation of LIHTC credits. We note first that federal law instructs the IRS to allocate LIHTC credits across states in proportion to each state's share of the U.S. population, with the total number of credits nationwide set by congress. Treating state population share as given, we assume that the total allocation

⁴LIHTC developers are obliged to fill 40 percent or more of their units with low-income families and are required to charge rents below a specified ceiling. Non-compliance with these terms results in forfeiture of future tax credits and also repayment of one-third of previously received allocations plus interest.

of credits to each state in the 1990s is also exogenous. Credits are then reallocated within state using whatever procedures each state deems appropriate in a given year (subject to federal guidelines for the overall program). Those procedures differ across states and over time, and we do not have direct data on individual state/year allocation procedures. Instead, we assume that states allocate their credits at least in part through a political process that mimics the federal government. Specifically, we assume that the allocation of credits within state between 1990 and 2000 is based partly on a given local area's (e.g. county) share of state population in 1990. Multiplying 1990 local population shares by the state allocation of LIHTC credits yields our first instrument for the number of LIHTC units in a given location.

As a second instrument, we allow for the possibility that cronyism may also influence within state allocations of the valuable LIHTC tax credits. Accordingly, for each county we code a dummy variable equal to 1 based on whether the county voted for the sitting Governor in 1989. Multiplying this measure by the first instrument described above allows for the possibility that communities that tend to vote for the winning gubernatorial candidate receive a greater than average share of state LIHTC credits relative to their share of population.

Additional details on the manner in which these two instruments are constructed are provided later in the paper. For now, it is sufficient to indicate that diagnostic tests indicate that the instruments are strongly correlated with LIHTC development (e.g. Stock and Yogo, 2005; Murray, 2006). In addition, tests of the overidentifying restrictions support the validity of the two instruments, although we view such tests with caution given their known tendency for weak power.

Our primary results are as follows. When considering areas up to five miles in radius, our findings indicate that roughly half of LIHTC development is offset by reductions in unsubsidized private construction of rental housing. When considering larger areas, as with 10-mile radius circles and county-level data, crowd out increases to roughly 100 percent. Together, these estimates suggest that while LIHTC development may affect the *location* of rental housing opportunities – encouraging some lower income families to gravitate to LIHTC enclaves within their broader communities or cities – the overall

impact of the program on the total stock of rental housing is small.⁵ We also find that crowd out effects of LIHTC development occur primarily in the rental sector of the market, and not the owner-occupied segment. Advocates of LIHTC development, therefore, need to look beyond expansion of the total stock of rental housing to justify the program.

To clarify our results, the paper proceeds as follows. The following section provides further detail on the institutional context of the LIHTC program, and also prior estimates of crowd out associated with place-based subsidized rental housing. Section 3 describes a simple conceptual model that guides our analysis. Section 4 describes our data and develops the empirical model used for the regression analysis. Section 5 presents the results, and Section 6 concludes.

2. Institutional Context and Prior Estimates of Crowd Out

This section provides a brief overview of some additional institutional details of the LIHTC housing program. Also included in this section is a review of previous research on crowd out associated with place-based subsidized housing.⁶

2.1 Institutional Context

Between 1937 and the late 1970's, low-income housing support was provided almost exclusively through public ownership and operation of housing built exclusively for low-income families. We refer here to such housing as “traditional public housing.”⁷ Typically, occupancy in these projects has been limited to families near or below poverty levels with tenants paying 30 percent of their gross income towards rent (Olsen, 2003).

⁵We also find, perhaps as might be expected, that LIHTC crowd out is concentrated in the rental as opposed to the owner-occupied sector of the market. Details are provided later in the paper.

⁶Exhaustive reviews of the LIHTC and other related housing programs are in Quigley (2000) and Olsen (2003).

⁷Olsen (2003) points out that there are at least 29 different public housing programs.

By the 1980s, two concerns about the public housing program had gained attention. The first was simply that the government builds, owns, and operates these projects: there are basic questions as to whether at least some portion of such activity is best left to the private market. In addition, because public housing projects were spatially concentrated and restricted occupancy to very low-income residents, they created dense clusters of poverty. Facilitated in part by several horrifying newspapers accounts, the public came to associate public housing with neighborhood decline, violent crime, and drug-use (Currie and Yelowitz, 2000). Concerns about adverse peer and neighborhood effects on children growing up in the projects also gained attention, both in academic and policy circles (see, for example, Currie and Yelowitz (2000) or Jencks and Mayer (1990)). Primarily for these reasons, the government stopped virtually all construction of traditional public housing in the early 1980's and began to demolish the worst performing projects during the 1990s.⁸ Figure 1 illustrates the construction of traditional public housing units since 1935 along with demolitions in the 1990s.

The LIHTC program was created as a part of the Tax Reform Act of 1986, both as an alternative to public housing and to offset the reform's removal of other tax benefits for owners of rental housing (U.S. Joint Committee on Taxation, 1987). As noted earlier, and different from other federal low-income housing programs, the LIHTC program is administered by the Internal Revenue Service under Section 42 of the U.S. Tax code.

The premise of the LIHTC program is to create a public-private partnership where the Federal Government subsidizes between 30 to 91 percent of non-land construction costs for private developers. In all cases, the subsidy is provided to developers through a 10-year stream of annual nonrefundable federal tax credits – dollar-for-dollar reductions in federal tax liability (Eriksen, 2007). In exchange for the subsidy, developers agree to set rents below specified ceilings and to lease a minimum specified share of the project's units to low-income families for at least 30 years. In practice, most projects contain 100

⁸In some instances, such as under the HOPE VI program, the structures were remodeled, but in most cases tenants were usually issued housing vouchers and told to seek housing privately (Jacob, 2004).

percent low-income occupancy owing to how the subsidy is structured and administered (see Eriksen (2007) for additional details).

It is also important to note that rent ceilings imposed on LIHTC units occupied by low-income families are effectively set at 18 percent of MSA median household income as determined by HUD.⁹ That amount is sufficiently high and the tax credits are sufficiently generous (30 to 91 percent), that LIHTC units are generally of high quality relative to most other low-income housing (Cummings and DiPasquale, 1999). It is also important to note that LIHTC occupants typically have a higher income than residents of traditional public housing (Wallace, 1995).¹⁰

These features of the public and LIHTC programs have implications for interpretation of our results to follow. Traditional public housing has suffered a particularly negative reputation over the years. This likely reduces demand for sites in close proximity to public housing projects, lowering property values. Such effects would tend to further discourage new development beyond impacts associated with crowd out. LIHTC developments, on the other hand, are high quality in comparison to other low-income housing, as noted above. In addition, many LIHTC developments “blend in” architecturally with their local communities (Buron et al., 2000). These features likely greatly reduce or even eliminate stigma effects associated with the presence of nearby LIHTC projects. As a result, our estimates of LIHTC crowd out will more closely reflect pure displacement effects as opposed to reductions in private housing construction arising from inward shifts in demand.

2.2 Previous estimates of crowd out from place-based subsidized housing

The possibility of crowd out arises any time government provides goods and services that are also offered through the private sector. This has been examined in a variety of markets, including health insurance, radio, and charitable giving (Culter and Gruber, 1996; Berry and Waldfogel, 1999; Andreoni

⁹The 18 percent limit is derived from two conditions imposed by the program. First, low-income families must earn incomes below 60 percent of MSA median income, and second, rent must not exceed 30 percent of that value.

¹⁰For example, Wallace (1995) estimates that only 28 percent of LIHTC residents earn below 50 percent of an area’s median income compared to 81 percent of those who reside in traditional public housing.

and Payne, 2003). Several recent studies have also begun to examine crowd out arising from place-based subsidized housing, although most do not consider the LIHTC program. The first of these by Murray (1983, 1999) utilizes national-level aggregate time series data from 1935 to the mid-1980s. These data pre-date the LIHTC program and are used to assess the impact of public and other earlier forms of subsidized rental housing construction on unsubsidized housing construction (Murray, 1983) and the equilibrium stock of housing (Murray, 1999). The general strategy of each paper is to examine whether construction of subsidized rental housing increases the total starts or stocks of housing on less than a one-for-one basis.¹¹ Evidence of such effects would be indicative of crowd out. Murray (1999) finds that subsidized rental housing programs that target very low income families generate only a small amount of crowd out. This is consistent with stylized facts that private market developers build little unsubsidized housing for very low-income families: for crowd out to occur, private markets must first be willing to provide the product. In contrast, Murray (1999) also estimates that between one-third to 100 percent of subsidized “moderate-income” place-based housing is offset by crowd out of unsubsidized construction. This is consistent with the idea that in the absence of construction subsidies, the private market would build at least some moderate income housing.

Given that LIHTC housing is approximately a moderate income housing program, this is important. But it should also be emphasized that Murray’s work differs from ours in two very important respects. First, our empirical design is based on cross-section data and relies on geographic and especially instrumental variable methods for identification. Murray’s work is based on aggregate time series data. Moreover, as noted above, Murray’s data reflect the impact of housing programs that pre-date the LIHTC program. Because those earlier programs have very different institutional arrangements than LIHTC development, there is no guarantee that Murray’s results would carry over to the LIHTC program.

More recently, and closer in structure to this paper, Sinai and Waldfoegel (2005) examine crowd out effects of place-based subsidized rental housing programs on per capita occupied housing units in

¹¹More precisely, Murray (1999) estimates the cointegrating relationship between the equilibrium stock of subsidized and unsubsidized housing stocks over the 1935 to 1987 period.

1990. When the data are measured at the census place level the OLS estimate of crowd out associated with place-based subsidized rental housing is roughly 70 percent.¹² When the data are aggregated to the MSA level, the point estimate of crowdout falls to roughly 30 percent. For both levels of geography, LIHTC housing is lumped in with other forms of place-based subsidized rental housing. This is important because the data used by Sinai and Waldfoegel (obtained from HUD's 1996 Picture of Subsidized Housing file) includes roughly 2.8 million place-based subsidized units. Of these, only 332,085 are LIHTC units, most of which were not present in 1990, the period associated with their dependent variable.¹³ As with Murray (1983, 1999), therefore, crowd out effects identified by Sinai and Waldfoegel (2005) reflect primarily crowd the impact of place-based programs that pre-date the LIHTC program.

Malpezzi and Vandell (2002) do consider directly the crowd out effects of LIHTC development. They analyze the impact of 1987-2001 state-level LIHTC allocations on the per capita stock of housing as measured in 2000 (based on the year-2000 census). Their point estimate implies full crowd out, although their sample is limited to just 51 state-level observations (including Washington, D.C.) with controls for 14 indicators of demand and supply. As a result, and as recognized by the authors, the standard error on their estimate of LIHTC effects is several times larger than their corresponding estimated crowd out effect. They are, therefore, unable to shed much light on the degree of crowd out associated with the LIHTC program.

Most recently, Baum-Snow and Marion (2007) examine the impact on LIHTC development given a census tract's qualified census tract (QCT) status as defined by HUD. QCT tracts are eligible for additional subsidies through the LIHTC program making these tracts especially attractive for LIHTC

¹²Sinai and Waldfoegel (2005) attempt to instrument for subsidized housing construction using the number of housing units per capita built before 1940 and also occupied public housing units per capita in 1980. However, results from the IV models yield quite different estimates of crowd out depending on which of the instruments are included. Partly for that reason, Sinai and Waldfoegel tend to emphasize their non-IV estimates of crowd out.

¹³Place-based subsidized units in the 1996 Picture files include Public (1,326,224 units) Section 8 Moderate Rehabilitation (105,845 units), Section 8 New Construction (897,160 units), Section 236 (447,382 units), and other place-based subsidized units (292,237 units). Additionally, the 1996 picture files only report roughly half of the LIHTC units allocated between 1987 and 1996 (Malpezzi and Vandell, 2002).

development, all else equal.¹⁴ Baum-Snow and Marion (2007) provide evidence that developers respond to a tract's QCT status by shifting development from adjacent tracts to the more heavily subsidized location. Although Baum-Snow and Marion discuss implications of their work for LIHTC crowd out of unsubsidized development, their primary focus is on the border region associated with QCTs and the response of developers to the more generous subsidy in those areas. Their finding underscores the tendency of developers to substitute capital across nearby neighborhoods in response to competing development opportunities. This further reinforces our argument in the Introduction that crowd out effects are most clearly identified at a relatively broad level of geography.

3. Conceptual Model

Consider now Figure 3a which portrays the market for the stock of rental housing at a given point in time. Abstracting from some of the details of the LIHTC program, the program subsidizes construction up to an exogenously given state-level allocation. This implies an outward shift in aggregate supply of rental housing, causing equilibrium rents to fall and housing stocks to increase.¹⁵

In Figure 3a, notice that the aggregate stock of rental housing increases by less than the level of LIHTC construction. In particular, whereas $H_3 - H_1$ equals the number of LIHTC units built, aggregate supply expands by only $H_2 - H_1$. The difference, $H_3 - H_2$, represents unsubsidized private construction that is "crowded out" by the LIHTC program. Moreover, Figure 3b illustrates that as the demand function becomes more inelastic crowd out becomes more pronounced. Indeed, the figures make clear that only

¹⁴LIHTC development in a QCT is eligible for a 30 percent increase in subsidy as compared to those not located in such a tract.

¹⁵Figures 3a and 3b suggest that the LIHTC program causes the entire supply function to shift out. This is a simplification that captures the dominant impact of the LIHTC program that is relevant to this paper while streamlining the discussion. An alternative and more accurate portrayal is that the LIHTC program flattens the slope of the lower most section of the supply curve up to the maximum number of LIHTC units allocated to a given location. Beyond that level of construction, the supply function steepens because additional investment is unsubsidized. Such a specification would imply that developers choose to invest first in LIHTC developments before unsubsidized construction. Moreover, to the extent that LIHTC development draws low-cost factor inputs away from the unsubsidized sector, input costs in the unsubsidized sector will be higher than in the absence of the LIHTC program. This would result in a further inward rotation of the unsubsidized segment of the supply function. See Olsen (2007) for a further discussion of this issue.

when housing demand is perfectly elastic or supply of newly constructed housing is perfectly inelastic would $H_3 - H_2$ equal zero and crowd out not occur.

To put this in perspective, Hanushek and Quigley (1980) use data from the housing allowance experiments of the 1970s to estimate the elasticity of demand for rental housing. For Pittsburgh and Phoenix their estimates are -0.36 and -0.41, respectively. For owner-occupied units, Rosen (1979) estimates a price elasticity of -0.99 for a random sample of owner-occupiers, while Rosenthal, Duca, and Gabriel (1991) obtain an estimate of -0.5 for FHA homebuyers, a group that is much closer in income to that of the typical renter. These estimates do not take location explicitly into account, and in that regard, are indicative of housing demand when considering a broad geographic region. Bearing that in mind, these estimates also confirm that when housing demand is not tied to a specific individual neighborhood, demand is far from perfectly elastic.

On the supply side, Mayer and Somerville (2000) estimate that the supply elasticity of newly built housing of all types is roughly 6. This is close to DiPasquale and Wheaton (1992) who estimate a supply elasticity for newly built multi-family rental housing of 6.8. Other estimates of the elasticity of supply of newly built housing are smaller, but generally well above 1 (e.g. DiPasquale, 1999; Rosenthal, 1999). While the range of supply elasticities is generally greater than on the demand side, both conceptual arguments and evidence in the literature nonetheless confirm that when considering expansion of the housing stock, supply is far from perfectly inelastic.¹⁶

Summarizing, only when housing demand is perfectly elastic or the supply of housing is perfectly inelastic would crowd out not occur. However, estimates in the literature strongly suggest that neither of these conditions hold, and especially when demand is not focused on a specific individual neighborhood.

¹⁶As a further perspective, suppose that developable land is plentiful, either as raw land or as previously developed land suitable for redevelopment. Suppose also that long run costs for building materials and labor are constant in real terms. Then home building is approximately constant returns to scale and new housing supply should be quite elastic (e.g. Rosenthal and Helsley, 1994). See also Glaeser and Gyourko (2005) for a discussion of the relative elasticity of supply with respect to expansion versus contraction of the stock of housing.

This suggests that on a qualitative basis, advocates and opponents of LIHTC development alike should anticipate crowd out from the program. The question then is, how much?

4. Data and Empirical Model

4.1 Data

Before developing our regression model it is useful to first highlight certain key features of the data. We use decennial census data aggregated to the census tract level as the root data source for our control variables. These data were obtained from the Geolytics, Inc. Neighborhood Change Database file for 1990 and 2000.¹⁷ Geolytics re-codes data from each of these years to year-2000 census tract boundaries. These data were combined with information on LIHTC projects placed into service up through 2000. The LIHTC data were obtained from HUD over the web.¹⁸ Information on the LIHTC database includes the year placed in service and the year-2000 census tract. Our data include 17,774 LIHTC projects containing 877,972 individual units.

Two points should be noted about these data. First, tracts are often rather small and for reasons outlined earlier, crowd out is more accurately identified over a larger geographic area. Second, geographic size differs from one tract to the next and that further complicates efforts to assess the geographic scope of crowd out. For both reasons, we conduct two sets of analysis. In the first, all of the data are further aggregated up to the county level, a geographic unit sufficiently large that substitution of households and housing capital across units is likely greatly reduced as compared to if one were to focus on small, individual neighborhoods. Analyzing at the county level, therefore, likely provides a good measure of the overall crowd out effects of the LIHTC program. However, by itself, county-level regressions do not shed light on the geographic scope of crowd out effects.

¹⁷See www.geolytics.com.

¹⁸See <http://lihtc.huduser.org> .

For our second set of analyses, we reorganize the data into uniform circular units using Geographic Information Systems (GIS) software (i.e. MapInfo and MapBasic). Data are recoded to circular geographic units of radius d miles drawn around the geographic centroid of the individual census tracts, i ($i = 1, \dots, n$). In all cases, this is done based on year-2000 census tract geography.¹⁹ The circle-based measures are produced for all of the dependent and independent variables. Circle-based measures were also used when measuring population shares used in constructing the instruments described earlier. Summary statistics of county-level data, and also for the 1-mile, 5-mile, and 10-mile circle data are provided in Table 3.²⁰ Configuring the data into circles allows us to examine the impact of different levels of geography (d) in a systematic manner while ensuring that each observation and both the dependent and independent variables are measured over areas of the same size.

4.2 Housing starts model

The conceptual model outlined above portrayed the impact of LIHTC development on the overall stock of housing. In that context, full crowd out would imply that LIHTC construction has no impact on the total number of housing units in the local economy. Sinai and Waldfogel (2005) draw on that intuition and specify their model so as to highlight the impact of subsidized rental housing programs on the total stock of occupied housing present at a given point in time. As noted in the Introduction, in our empirical work to follow, we take a different but closely related approach. Specifically, we condition on the lagged level of housing stock and assess the impact of LIHTC development on changes in the stock of housing between 1990 and 2000. In this context, full crowd out would imply that every LIHTC unit built would reduce the change in private unsubsidized housing stocks by one unit. While these two

¹⁹MapInfo and MapBasic were used to manipulate the geographic features of the data. When drawing circles around the census tract centroids, proportional sum measures were used to calculate the various count variables.

²⁰Although we estimate and report estimates using 2, 3, and 4-mile circle data as well, we do not report the summary measures for those data to conserve space.

perspectives on crowd out are closely related, a focus on flows conditional on lagged stocks offers advantages given the nature of our data as outlined in the Introduction.

Specification of our model is guided by previous work on housing starts, and especially that of Mayer and Somerville (2000).²¹ Mayer and Somerville emphasize that new housing construction is a flow, and for this reason, is best expressed as a function of changes in housing prices and costs rather than as a function of the levels of those factors. They also recognize that deterioration of the existing housing stock provides a further motivation for new housing development.

Mayer and Somerville estimate their model using quarterly aggregate time series data for the U.S.. Housing starts between periods t and $t-1$ are expressed as a function of change in quality adjusted house prices, change in the real interest rate, change in the cost of building materials, the lagged median time on the market among homes for sale, and the lagged level of the existing housing stock.²² The interpretation of these control measures is mostly straight forward. Rising prices encourage developers to tap into increasingly expensive factor inputs and increase supply, while rising interest rates and building costs increase the cost of development and have the opposite effect. Longer time on the market for unsold homes signals an increase in inventories that would likely discourage developers from starting new homes. A larger initial stock of housing is likely associated with a greater number of older homes that have become dilapidated or stylistically obsolete, and as such are ripe for replacement. Larger initial stock levels may also reflect the influence of other unobserved factors that drive housing demand and supply.

Our goal is to estimate a model that takes account of the features above, customized to the nature of our data and the timing of the LIHTC program. Adding LIHTC development to the model will then allow us to assess the crowd out effects of the program. As will become apparent, this requires that we

²¹Other important housing supply models include the stock adjustment model of Topel and Rosen (1988) and related work by DiPasquale and Wheaton (1994).

²²Mayer and Somerville (2000) also allow for an AR(1) term and a time trend that help to soak up the influence of unobserved factors. As will become apparent below, we also allow for serial correlation for similar reasons. Our focus on a single cross-section eliminates any issue of time trends.

address two difficult empirical challenges. The first challenge is that several key drivers of housing starts are difficult if not impossible to directly measure, while the second is that key control measures, including LIHTC development, may be endogenous. These issues will each be addressed in turn.

As a starting point, we express housing starts between 1990 and 2000 (the time period of our data) in a given location as follows,

$$s_d^{rental,unsubsidized} = b_1 \Delta p_d^{Q-adjusted} + b_2 S_{d,1990} + b_3 \Delta rate + b_4 \Delta q_r^{Non-LandInputs} + b_5 S_{d,1990}^{rental,vacant} + \varepsilon_d \quad (3.1)$$

In (3.1), the subscript d denotes the location in question, while r is the broader geographic region in which d is situated. This distinction allows us to use region fixed effects to control for some variables, as will be clarified shortly. Recall also, that we code geography in two different ways. Initially, we let d denote a given county. In this instance, we treat the MSA in which the county is located as the broader region, denoted by r , provided the county is in an MSA. For counties not in MSAs, r is coded as the state in which the county is situated. In separate regressions we also code the data to circles. In this case, d is set to a circle of radius 1 to 10 miles depending on the regression in question. Moreover, for these regressions, r is always set to the county in which the center of a given circle is located.

Defining d and r in this manner allows us to control for the underlying drivers of housing starts noted above. To clarify, note first that the dependent variable, $s_d^{rental,unsubsidized}$, is the number of unsubsidized rental housing starts between 1990 and 2000 and clearly varies with location, d . The term $S_{d,1990}$ is the lagged total number of housing units (rental plus owner-occupied) in d in 1990. As noted earlier, lagged housing stock levels likely control for a host of unobserved local factors that might otherwise bias our estimates of LIHTC effects. Moreover, by conditioning on lagged housing stocks, our dependent variable necessarily reflects the change in housing stocks between periods. The term $S_{d,1990}^{rental,vacant}$, meanwhile, is the number of vacant rental units in 1990 and allows for possible disequilibrium conditions in that year. These terms all vary with d . Moreover, all three of the variables

just noted can be readily measured for each treatment of geography using the root census tract data described earlier.

To further enrich our specification we decompose $S_{d,1990}$ into separate components for housing built in the 1980s, housing built in the 1970s, and housing built prior to 1970. Moreover, we include separate measures for of each of these terms for the rental and owner-occupied stocks of housing. Accordingly, we rewrite (3.1) as,

$$\begin{aligned}
S_d^{rental,unsubsidized} &= b_1 \Delta p_d^{Q-adjusted} \\
&+ b_{2,1}^{rent} S_{d,1990}^{rent,80to90} + b_{2,2}^{rent} S_{d,1990}^{rent,70to80} + b_{2,3}^{rent} S_{d,1990}^{rent,pre70} \\
&+ b_{2,1}^{own} S_{d,1990}^{own,80to90} + b_{2,2}^{own} S_{d,1990}^{own,70to80} + b_{2,3}^{own} S_{d,1990}^{own,pre70} \\
&+ b_3 \Delta rate + b_4 \Delta q_r^{Non-LandInputs} + b_5 S_{d,1990}^{rental,vacant} + \varepsilon_d
\end{aligned} \tag{3.2}$$

Including the 1990 age distribution of the housing stock for both rental and owner-occupied housing has several advantages over the specification in (3.1). To the extent that unobserved local drivers of housing starts are serially correlated, the terms related to housing developed in the 1980s will tend to soak up such effects (e.g. $S_{d,1990}^{rent,80to90}$). In effect, we allow for an AR(1) process as in Mayer and Somerville (2000). At the same time, older housing stocks present in 1990 (e.g. housing built prior to 1970, such as $S_{d,1990}^{rent,pre70}$) would be subject to increasing deterioration as the 1990s wore on. As a result, these stocks would be increasingly ripe for replacement and their presence might lead to more housing starts in the 1990s. To the extent that rental and owner-occupied markets are close substitutes, distinguishing between these two sets of housing stocks would have little impact. But a more likely pattern is that rental and owner-occupied housing are only weak substitutes, in which case we would expect much stronger effects associated with the lagged rental as opposed to owner-occupied stocks.

Of the remaining terms in (3.1), $\Delta rate$, the change in the real interest rates, is the simplest to take into account. This term is assumed to be common across all locations during the 1990s. As we estimate using a single cross section, $\Delta rate$ becomes a constant in (3.2). In a similar vein, the term

$\Delta q_r^{Non-LandInputs}$ represents the change in the price of non-land factor inputs (materials and labor).

Importantly, we assume that this term varies across regions but is constant within a given r . This seems reasonable as an approximation. Given this assumption, we can remove the influence of

$\Delta q_r^{Non-LandInputs}$ by including region fixed effects in the model.

That leaves just $\Delta p_d^{Q-adjusted}$, a term that represents the change in quality-adjusted house prices between 1990 and 2000 in location d . If we are willing to assume that the growth in house prices is constant across locations within a given region, then including region fixed effects in the model would difference away this term as well. For two reasons, however, this is not an appealing assumption. First, demand shocks could easily differ across locations even within the defined broader regions. This seems especially possible when d is small relative to r (e.g. when d is set to a 1-mile circle and r to the county). Second, different locations may be in different states of housing market disequilibrium in 1990 relative to the long run as reflected in differing vacancy rates. This would further contribute to differences at the local level in the degree to which house prices might change over the 1990s. We resolve this problem by proxying for $\Delta p_d^{Q-adjusted}$ as follows,

$$\begin{aligned} \Delta p_d^{Q-adjusted} \approx & a_1 \Delta Pop_d + a_2 \Delta MedInc_d \\ & + a_3 \Delta Pop_d \cdot S_{d,1990}^{rental,vacant} + a_3 \Delta MedInc_d \cdot S_{d,1990}^{rental,vacant} \\ & + a_4 D + \delta_r \end{aligned} \quad (3.3)$$

In (3.3), the region fixed effect, δ_r , captures the region wide change in quality-adjusted house prices. The remaining terms reflect deviations from the mean effect for individual locations. The term ΔPop_d is the change in population in location d between 1990 and 2000. Similarly, $\Delta MedInc_d$ is the change in median family income in location d . These two terms are fundamental drivers of shifts in demand and should have a positive impact on changes in price at the local level. However, the degree to which that occurs is likely sensitive to the number of vacant units in 1990. When large numbers of vacant units are present, a positive demand shock can be at least partly accommodated by filling up vacant units,

and this will mitigate upward pressure on price. For this reason, the interactive terms in (3.3) should have a negative impact on price. Demand shocks likely also vary systematically with a given location's distance from the city center. This is because cities tend to develop and subsequently redevelop from the center outwards over time (e.g. Brueckner and Rosenthal (forthcoming)). To allow for this pattern, the term D_d denotes the distance to the city center in models where geographic units are measured as circles, and density (number of housing units divided by land area) when we instead use county-level data.²³

Substituting (3.3) into (3.2) and reordering some of the variables to facilitate review we obtain,

$$\begin{aligned}
S_d^{rental,unsubsidized} = & b_1^{rent} S_{d,1990}^{rent,80to90} + b_2^{rent} S_{d,1990}^{rent,70to80} + b_3^{rent} S_{d,1990}^{rent,pre70} \\
& + b_3^{own} S_{d,1990}^{own,80to90} + b_4^{own} S_{d,1990}^{own,70to80} + b_5^{own} S_{d,1990}^{own,pre70} \\
& + b_6 S_{d,1990}^{rental,vacant} + b_7 \Delta Pop_d + b_8 \Delta MedInc_d \\
& + b_9 \Delta Pop_d \cdot S_{d,1990}^{rental,vacant} + b_{10} \Delta MedInc_d \cdot S_{d,1990}^{rental,vacant} \\
& + b_{11} D_d + \lambda_r + \varepsilon_d
\end{aligned} \tag{3.4}$$

Expression (3.4) captures the primary features associated with housing starts models in the literature.²⁴

Augmenting this equation with the number of LIHTC units built between 1990 and 2000 (denoted s_d^{LIHTC}) yields our primary estimating equation,

$$\begin{aligned}
S_d^{rental,unsubsidized} = & \theta s_d^{LIHTC} + b_1^{rent} S_{d,1990}^{rent,80to90} + b_2^{rent} S_{d,1990}^{rent,70to80} + b_3^{rent} S_{d,1990}^{rent,pre70} \\
& + b_3^{own} S_{d,1990}^{own,80to90} + b_4^{own} S_{d,1990}^{own,70to80} + b_5^{own} S_{d,1990}^{own,pre70} \\
& + b_6 S_{d,1990}^{rental,vacant} + b_7 \Delta Pop_d + b_8 \Delta MedInc_d \\
& + b_9 \Delta Pop_d \cdot S_{d,1990}^{rental,vacant} + b_{10} \Delta MedInc_d \cdot S_{d,1990}^{rental,vacant} \\
& + b_{11} D_d + \lambda_r + \varepsilon_d
\end{aligned} \tag{3.5}$$

In this expression, θ is the primary variable of interest. If its coefficient equals 0 that would indicate that construction of LIHTC units has no effect on the number of private, unsubsidized rental

²³In the circle regressions, we restrict the analysis to just those core census tracts in MSAs, and define the city center as the geographic centroid of the census tract with the highest population density in 2000.

²⁴Note that λ_r captures the influence of all region-specific effects, including changes in real interest rates, changes in non-land factor price inputs, and changes to the common component to price movements (δ_r from (3.3)).

housing units built between 1990 and 2000. If instead, θ equals -1 that would imply complete crowd out and indicate that LIHTC construction does little to increase the overall stock of rental housing.

4.3 Endogenous variables

Two sets of variables in (3.4) seem especially prone to being endogenous. The first is the key control variable, LIHTC housing development. The second are the controls for the change in population and median income in location d between 1990 and 2000. We consider these latter variables first.

New housing construction in a given location has the potential to *attract* families, in addition to serving the needs of households choosing the location for exogenous reasons. Similarly, construction of rental housing may attract lower income families seeking such housing opportunities. For both reasons, it is possible that the change in population and median income in a given location could be endogenous to new housing development. To address this concern, we measure the change in population (median income) in location d by multiplying the 1990 population (median income) level in d by the percentage growth in population (median income) for a broader geographic area. When setting d to county-level geography, we use the state-level percentage change in population and median income to scale the county-level measures from 1990. When setting d to circle-level geography, we use the MSA-level percentage change in population and median income for the MSA in which the circle center is located. In both cases, we make two assumptions: (i) the 1990 population and median income level in location d is exogenous to housing development between 1990 and 2000, and (ii) the percentage change in population and median income at the state and MSA levels is exogenous to county- and circle-level construction of new housing in the 1990s, respectively. The first assumption is really no different than assuming that the stock of housing in 1990 is exogenous, an assumption already implicit in the housing starts model, (3.1). The second assumption is equivalent roughly to arguing that development in a small geographic unit would not noticeably affect the overall rate of population and income growth for a much larger geographic area.

A different strategy is employed to control for the possibly endogenous placement of LIHTC units. We estimate our models by two-stage least squares and instrument LIHTC development in the manner described in the Introduction. Specifically, recall that federal law instructs the IRS to allocate LIHTC credits across states in proportion to each state's share of the U.S. population, with the total number of credits nationwide set by congress. Treating state population share as given, we assume that the total allocation of credits to each state in the 1990s is also exogenous. It seems likely that states allocate their credits at least in part through a political process that mimics the federal government. Accordingly, as noted earlier, we assume that the allocation of credits within state between 1990 and 2000 is based partly on a given local area's (e.g. county) share of state population in 1990. Multiplying 1990 local population shares by the state allocation of LIHTC credits yields our first instrument for the number of LIHTC units in a given location.

Also as noted earlier, for our second instrument we allow for the possibility that cronyism may further influence within state allocations of the valuable LIHTC subsidies. Accordingly, for each county we code a dummy variable equal to 1 based on whether the county voted for the sitting Governor in 1989.²⁵ Multiplying this measure by the first instrument described above allows for the possibility that communities with a history of voting for the winning gubernatorial candidate during the initial years of the LIHTC program received a greater share of tax credits throughout the 1990s.

4.4 Overlapping circles

A final empirical issue concerns the overlapping nature of the circles when d is set to circle areas. Recall that the circle measures ensure a common size for each sampled area and are drawn around the geographic centroids of the underlying census tracts. This implies that nearby circles will often overlap. For the independent variables such overlap presents no special problems. But for the dependent variables

²⁵County-level election results for Governor from 1985-1988 were obtained from the data series "General Election Data for the United States, 1950-1990" produced by Inter-University Consortium for Political and Social Research (ICPSR).

overlapping circles cause the underlying census tract information to be repeated across observations. Failing to address that issue would cause the standard errors from the model to be biased downwards but would not bias the coefficient estimates.

A convenient solution to this problem is available. Specifically, when measuring our variables in circles, we cluster the standard errors at the county level, consistent with our inclusion of county-level fixed effects. This allows for repetition of information across dependent variables for observations centered in the same county. In instances where circle overlap is limited, clustering in this manner likely overcompensates for the problem. This would cause our estimation procedure to be inefficient but would not affect the consistency of the crowd out estimates.

5. Results

5.1 County-level analysis

Table 4 presents OLS and 2SLS estimates for the county-level model based on several different specifications that differ in their treatment of the LIHTC variable. Recall that for counties within MSAs we include fixed effects and cluster at the MSA level. For counties outside of MSAs, the fixed effects and clusters are based on the state in which the county is located.²⁶ Given these fixed effects, we drop counties that comprise one-county MSAs. It should also be emphasized that in all cases, counties are drawn from throughout the U.S. yielding a sample of just over 3,000 observations.

Consider first the coefficients on the terms other than LIHTC development. Reading across the columns, the first point to recognize is that the coefficients on these variables differ little regardless of how LIHTC is entered into the regression. This pattern will be echoed when we vary geography in the tables to follow.

OLS estimates are presented in the first column of Table 4. The evidence suggests a strong pattern of first-order serial correlation in rental housing starts. Among rental units present in 1990, the

²⁶Dropping the non-MSA counties had little impact on the results and for that reason results from those models are not reported.

coefficient on those built in the 1980s is 0.3 with a t-ratio of 3.23. For rental units built in the 1970s and also prior to 1970, the corresponding coefficients are essentially zero. Observe also, that the corresponding estimates on the 1990 stock of owner-occupied housing are always small: the coefficient on units built in the 1980s, for example, is just 0.069 with a t-ratio of 1.16, for example. These patterns suggest that unobserved trends that contribute to county-level rental housing construction in the 1980s tend to persist into the 1990s. In addition, as anticipated, rental housing construction is far more sensitive to existing rental housing stocks as compared to existing stocks of owner-occupied housing. This is consistent with the idea that housing markets are heavily segmented between the rental and owner-occupied sectors.

Change in population and median income are both associated with positive effects on rental housing construction in the 1990s. In the case of population, the coefficient is precisely estimated, with a t-ratio of 3.19. The corresponding t-ratio for the change in median income is 1.60. Moreover, whereas the interaction between the income variable and rental vacancies is clearly insignificant (a t-ratio of 0.36), the interaction for the population variable is negative and significant, with a t-ratio of 2.10. These results indicate that, at least in the case of population, growth increases rental housing construction, but less so to the extent that there are more vacant rental units present in 1990.

As the remaining non-LIHTC variables are largely insignificant, we turn now to the impact of LIHTC development in the 1990s.²⁷ In the OLS model, the coefficient on LIHTC construction is -0.051 with a t-ratio of 0.16. Taken at face value, this estimate would suggest the absence of crowd effects from LIHTC development. However, such a conclusion would be premature.

The second and third columns of Table 4 present 2SLS estimates of the model using first the population share instrument and then the interaction instrument that allows for cronyism. The fourth

²⁷Although vacancies have a further direct negative effect in the OLS model (a coefficient of -0.158 with a t-ratio of 1.24), the corresponding coefficient is nearly equal to zero when treating LIHTC housing as endogenous. In addition, there is no evidence in any of the models in Table 4 that density has a discernible effect.

column in the table includes both instruments and is overidentified given that we have just one endogenous regressor. We consider first the diagnostics associated with the validity of the instruments.

At the bottom of the table, note that the first stage coefficients on the included instruments are positive and highly significant in each of the models. In the far right column where both instruments are included in the model, the first-stage t-ratios on the population share and cronyism instruments are 3.82 and 4.26, respectively. Notice, also, that the Kleibergen-Paap statistic used to further test for weak instruments is 18.76, well above the “10” often used to assess whether weak instrument bias is a serious problem (e.g. Stock and Yogo (2005); Murray (2006)). Analogous first-stage diagnostics are obtained when the instruments are entered individually in the middle two columns. Overall, we conclude that our instruments appear to be strong, and our models are unlikely to be subject to weak instrument bias.²⁸

In principle, it is also possible to test whether the overidentifying restrictions in the fourth column can be rejected. Evidence that the overidentifying restrictions are invalid would be indicative of model misspecification. Results from a Hansen-J test indicate a P-value of 0.6208, and suggest that we cannot reject the null that the model and instruments are properly specified. While encouraging, we caution that the Hansen-J test is known to be sensitive to model specification and to have weak power. This is especially true when the mechanism for why the instruments are correlated with the endogenous variable is similar, as is clearly the case here given that both instruments draw on population shares as noted (e.g. Davidson and McKinnon (2004); Cameron and Trivedi (2006); Murray (2006)).

Having determined that the instruments are strong, and assuming exogeneity, we turn to the coefficients of primary interest. The coefficients on LIHTC development in the second and third models are -1.2886 and -0.7911, respectively, with t-ratios of 1.58 and 1.11. In the fourth column, the coefficient is -0.9811 with a t-ratio of 1.78. The similarity of the three point estimates offers further support for the two instruments: in the event that both instruments are valid, then the coefficients from the three 2SLS

²⁸Formal critical values for weak instrument tests have yet to be developed for the case where the standard errors are allowed to be heteroscedastic, as is the situation here in that we cluster the standard errors (see, for example, Stock and Yogo (2005)). Nevertheless, the evidence at the bottom of Table 4 is quite suggestive that weak instrument bias is not a problem.

models should converge asymptotically to the same value. Given this result we believe the fourth column is the most reliable as it draws on variation from both instruments and clearly also yields a more precise estimate of the coefficient on LIHTC activity.

In column 4, it is apparent that the 2SLS model indicates essentially complete crowd out. For every 100 LIHTC units built over the 1990s, the estimate implies that 98 fewer unsubsidized rental units were built in the county over the same period. Moreover, the much less negative OLS estimate is suggestive that developers tend to endogenously site LIHTC projects in counties that receive unusually high levels of unsubsidized rental development conditional on the model control variables. Failing to take that into account would mask the crowd out effects evident in the 2SLS model and mistakenly cause one to perceive that crowd out is absent.

5.2 Circle-level analysis

The estimates in Table 4 are striking. At the same time, they offer relatively little guidance as to the geographic dimension of possible crowd out effects. Accordingly, we turn now to the more geographic based analysis, with the data coded to circles of different size as discussed earlier. Restricting our sample to circle units whose centroids are located in MSAs, we now have a sample of roughly 50,000 observations, many times larger than the county-level analysis in Table 4.²⁹ Recall also that we now include county fixed effects (roughly 850 in all) and further cluster the standard errors at the county level.

Bearing these features in mind, OLS results for the circle models are provided in Table 5, while 2SLS estimates are in Table 6. For both tables, each column corresponds to a different underlying geographic unit of analysis, from 1- to 10-mile radius circles. In addition, all of the 2SLS models in Table 6 include both instruments in the first stage. As before, we begin by commenting briefly on the variables other than LIHTC development.

²⁹We restrict the sample to locations within MSAs for two reasons. First, the underlying census tracts are smaller in MSAs and this helps to reduce measurement error when recoding the data to circles. Second, MSAs have well defined centers allowing us to include distance to the MSA center as a control variable.

Consistent with the county-level analysis, notice that the coefficients on the lagged housing stocks are quite similar across models regardless of whether the estimation is by OLS or 2SLS, and regardless of the size of the geographic units used in the analysis. The stability of estimates across geographic units of analysis likely arises because a change in the geographic scope of the units analyzed has an equal proportional effect on the number of LIHTC units built and the existing stock of housing.

Results for the other terms other than LIHTC construction are also similar across models, but with some relatively minor differences. Focusing on the 2SLS results in Table 6, as before, increases in population and median income increase private rental housing construction, with the median income variable particularly significant for all sizes of circle geography. Also as before, these effects are dampened when larger numbers of vacant rental units are present in 1990. It is also evident that distance from the city center is associated with reduced private rental housing construction.

Table 7 collects and displays the OLS and 2SLS coefficients on LIHTC construction from Tables 5 and 6 to facilitate comparisons across specifications. Also reported at the bottom of Table 7 are the first-stage diagnostics on the instruments. By and large, the first stage diagnostics look good. The first stage t-ratios on the instruments are all well above 2 except for the 10-mile circle regressions for which the t-values are 1.95 and 1.84. The Kleibergen-Paap F-statistics are over 20 in each model except again for the 10-mile circle regression, for which the test statistic is 11.24. The Hansen-J test P-values range from 0.55 to 0.32 for circles one to five miles in radius, and 0.128 for the 10-mile circle. Overall, these diagnostic tests indicate that the instruments are strong. We also do not see evidence suggestive of model misspecification (e.g. the Hansen-J tests), but again, we view the Hansen-J tests with caution.

Reviewing the estimates of LIHTC crowd out in Table 7 reveals several interesting patterns. First, note that the OLS and 2SLS estimates are quite similar for the 1- to 5-mile circle analyses, but differ sharply for the larger, 10-mile circle regression. For the narrower circle regressions, LIHTC crowd out is roughly 50 percent, and statistically significant except for the 2SLS models for circle areas 3- to 5-miles in radii. For the 10-mile circle regressions, the OLS estimate is -0.1995 (with a t-ratio of 1.10), close to the OLS estimate from the county-level regression in Table 4. The corresponding 2SLS estimate is -

1.069 (with a t-ratio of 2.31), also close to its counterpart in Table 4. Thus, when we expand the size of the underlying units of analysis to 10 mile radius circles, our estimates largely converge to that of the county-level regressions despite the very different samples, fixed effects, and clustering.

A further point should be emphasized regarding the results in Table 7. For narrower levels of geographic analysis, crowd out is roughly 50 percent, but when the geography of the underlying units of analysis is expanded, crowd out increases to 100 percent. This pattern is consistent with our conceptual framework earlier in the paper: housing demand is more inelastic when viewed over a larger unit of geography, and this serves to increase the perceived crowd out effects of the LIHTC program. On balance, the estimates in Table 7 suggest that LIHTC crowd out is large, and that a focus on individual neighborhoods might well cause one to underestimate the degree to which LIHTC development displaces unsubsidized rental housing construction.

5.3 Owner-occupied construction

Our discussion thus far has focused exclusively on the impact of LIHTC development on unsubsidized rental housing construction. This is natural, but also incomplete. To the extent that rental and owner-occupied segments of the housing market interact, it is possible that LIHTC development could also displace construction of owner-occupied units. We consider this possibility by substituting construction of owner-occupied housing in the 1990s for construction of private rental housing as the dependent variable in the regression model. In addition, we replace the rental vacancy and related interactive terms with vacancy measures based on the owner-occupied units. All other features of the model are as before.

Table 8 presents results for LIHTC impacts of owner-occupied housing construction for the 1- to 10-mile circle specifications, formatted in the same manner as Table 7. The OLS estimates are generally relatively small, positive, and significant, with the 10-mile coefficient unusually large at 0.49. The 2SLS estimates are very small for the regressions based on circles sized 1-mile to 4 in radii, and completely

insignificant. For the 5-mile and 10-mile circle regressions, the 2SLS estimates are -0.3071 and -0.6877 with t-ratios of roughly 0.8 in both cases.

Three important patterns should be highlighted here. First, the OLS bias suggests that developers site LIHTC units in locations that tend to receive unusually large amounts of owner-occupied development. This is consistent with patterns in several of the rental models, especially when larger geographic units were being analyzed. Second, there is some evidence in the 2SLS estimates of increasing crowd out as the geographic unit of analysis is increased. This also reinforces the pattern found for the rental sector. Third and most important, the degree to which LIHTC development displaces owner-occupied construction is considerably muted relative to effects on unsubsidized rental housing.

6. Conclusion

The recent dramatic growth of the Low-Income Housing Tax Credit (LIHTC) program has caused an old question to gain new importance. Should government provide low-income housing support through tenant- or placed-based programs? In that context, the LIHTC program has ballooned since its inception in 1987, and is now the largest subsidized rental housing construction program in U.S. history. The program subsidizes 30 to 91 percent of construction costs for eligible projects, 44 percent of which are located in middle- and higher-income neighborhoods, and has accounted for one-third of all multi-family rental housing construction in recent years. Moreover, recent proposals in Congress have sought to double the size of the program. Nevertheless, little is known about the efficacy of this increasingly important and expensive program. This paper has sought to fill part of that gap.

Our most important finding is that displacement of private rental housing construction as a result of the LIHTC program is substantial. When considering areas up to 5 miles in radius, our estimates indicate that roughly half of LIHTC development is offset by displacement of unsubsidized construction of rental units. For larger geographic units, as with 10-mile radius circle areas or entire counties, crowd out of unsubsidized rental construction from LIHTC development is nearly 100 percent. Moreover, although the confidence bands around our estimates of LIHTC crowd out allow for debate about the

precise level of crowd out, they are sufficiently tight as to confirm that crowd out effects are large. Our estimates also confirm that these effects occur primarily in the rental sector of the housing market, with limited evidence of LIHTC impacts on construction of owner-occupied units.

These findings suggest that proponents of the LIHTC program need to look beyond simple expansion of the overall stock of rental housing to justify the program's continuance. One possibility is that LIHTC development may affect the location of where low-moderate rental housing opportunities are found. Summary measures, for example, indicate that 16 percent of LIHTC projects have been built in neighborhoods in the upper third of their MSA's income distribution, and another 28 percent in communities in the middle third of the income distribution. We leave this as an area for further research.

References

- Andreoni, J., Payne, A., 2003. Do Government Grants to Private Charities Crowd Out Giving or Fundraising? *The American Economic Review*, 93 (3), 792-812.
- Baum-Snow, N., Marion, J., 2007. The Effects of Low Income Housing Developments on Neighborhoods. Brown University working paper, mimeo.
- Berry, S., Waldfoegel, J., 1999. Public Radio in the United States: Does it Correct Market Failure or Cannibalize Commercial Stations? *Journal of Public Economics* 71, 189-211.
- Brueckner, J., Rosenthal, S., forthcoming. Gentrification and Neighborhood Cycles: Will America's Future Downtowns Be Rich? *Review of Economics and Statistics*, 47 pages.
- Buron, L., Nolden, S., Heintz, K., Stewart, J., 2004. Assessment of the Economic and Social Characteristics of LIHTC Residents and Neighborhoods. Department of Housing and Urban Development working paper.
- Cameron, C., Trivedi, P., 2006. *Microeconometrics: Methods and Applications*. New York: Cambridge University Press.
- Culter, D., Gruber, J., 1996. Does Public Insurance Crowd Out Private Insurance. *Quarterly Journal of Economics* 111 (2), 391-430.
- Currie, J., Yelowitz, A., 2000. Are Public Housing Projects Good for Kids? *Journal of Public Economics* 75, 99-124.
- Cummings, J., DiPasquale, D., 1999. The Low-Income Housing Tax Credit: The First Ten Years. *Housing Policy Debate* 10 (2), 257-267.
- DiPasquale, D., 1999. Why Don't We Know More About Housing Supply? *Journal of Real Estate Finance and Economics* 18, 9-21.
- DiPasquale, D., Fricke, F., Garcia-Diaz, D., 2003. Comparing the Costs of Federal Housing Assistance Programs. *FRBNY Economic Policy Review* June, 147-165.
- DiPasquale, D., Wheaton, W., 1992. The Cost of Capital, Tax Reform and the Future of the Rental Housing Market. *Journal of Urban Economics* 31 (3), 337-359.
- DiPasquale, D., Wheaton, W., 1994. Housing Market Dynamics and the Future of Housing Prices. *Journal of Urban Economics* 35, 1-28.
- Eriksen, M., 2007. Neighborhoods, Risk, and the Value of Low-Income Housing Tax Credits. Center for Policy Research Working Paper.
- Glaeser, E., Gyourko, J., 2005. Urban Decline and Durable Housing. *Journal of Political Economy* 113, 345-375.
- Hansen, L., 1982. Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica* 50, 1029- 1054.

- Hanushek, E., Quigley, J., 1980. What Is the Price Elasticity of Housing Demand? *Review of Economics and Statistics* 62, 449–54.
- Jencks, C., Mayer, S., 1990. The social consequences of growing up in a poor neighborhood. In: Lynn, L., McGeary, M. (Eds.), *Inner-city Poverty in the United States*, Washington: National Academy Press, 111–186.
- Malpezzi, S., Vandell, K., 2002. Does the low-income housing tax credit increase the supply of housing? *Journal of Housing Economics* 11 (4), 360-380.
- Mayer, C., Somerville, T., 2000. Residential Construction: Using the Urban Growth Model to Estimate Housing Supply. *Journal of Urban Economics* 48, 85-109.
- Murray, M., 1983. Subsidized and Unsubsidized Housing Starts: 1961-1977. *Review of Economics and Statistics* 65 (4), 590-597.
- Murray, M., 1999. Subsidized and unsubsidized housing stocks 1935 to 1987: Crowding Out and Cointegration. *Journal of Real Estate Finance and Economics* 18, 107–124.
- Murray, M., 2006. Avoiding invalid instruments and coping with weak instruments. *Journal of Economic Perspectives* 20, 111–32.
- Olsen, E., 2003. Housing Programs for Low-Income Households. In: Moffit, R. (Ed.). *Means-Tested Transfer Programs in the U.S.*. National Bureau of Economic Research. Chicago: University of Chicago Press.
- Olsen, E., 2007. A Review of [A Primer on U.S. Housing Markets and Housing Policies](#). *Regional Science and Urban Economics* 37, 618-624.
- Quigley, J., 2000. A Decent Home: Housing Policy in Perspective. *Brookings-Wharton Papers on Urban Affairs*. 1 (1), 53–100.
- Rosen, H., 1979. Housing Decisions and the U.S. Income Tax. *Journal of Public Economics* 11, 1-23.
- Rosenthal, S., Duca, J., Gabriel, S., 1991. Credit Rationing and the Demand for Owner-Occupied Housing. *Journal of Urban Economics* 29, 48-63.
- Rosenthal, S., Helsley, R., 1994. Redevelopment and the Urban Land Price Gradient. *Journal of Urban Economics* 35, 182–200.
- Rosenthal, S., 1999. Housing Supply: The Other Half of the Market. A Note from the Editor. *Journal of Real Estate Finance and Economics* 18, 5-8.
- Rosenthal, S., 2008. Old Homes and Poor Neighborhoods: A Model of Urban Decline and Renewal. *Journal of Urban Economics* 63 (3), 816-840.
- Sinai, T., Waldfoegel, J., 2005. Do low-income housing subsidies increase the occupied housing stock? *Journal of Public Economics* 89, 2137-2164 .

- Stock, J., Wright, J., Yogo, M., 2002. GMM, Weak Instruments, and Weak Identification. *Journal of Business and Economic Statistics* 20, 518–530.
- Topel, R., Rosen, S., 1988. Housing Investment in the United States. *Journal of Political Economy* 96, 718-740.
- U.S. Congress, Joint Committee on Taxation. 1987. General Explanation of the Tax Reform Act of 1986. 100th Congress, 1st Session, 152.
- U.S. Congress, Joint Committee on Taxation. 2005. Committee Prints, 109th Congress, Estimates of Federal Tax Expenditures for Fiscal Years 2005-2009, JCS-1-05.
- U.S. Department of Treasury, Internal Revenue Service, Internal Revenue Code, Section 42.
- Wallace, J., 1995. Financing Affordable Housing in the United States. *Housing Policy Debate* 6, 785-814.
- Woolridge, J., 2003. Cluster-Sample Methods in Applied Econometrics. *The American Economic Review* 93 (2), 133-138.

Figure 1. Place-Based Subsidized Construction and Demolitions of Housing Units

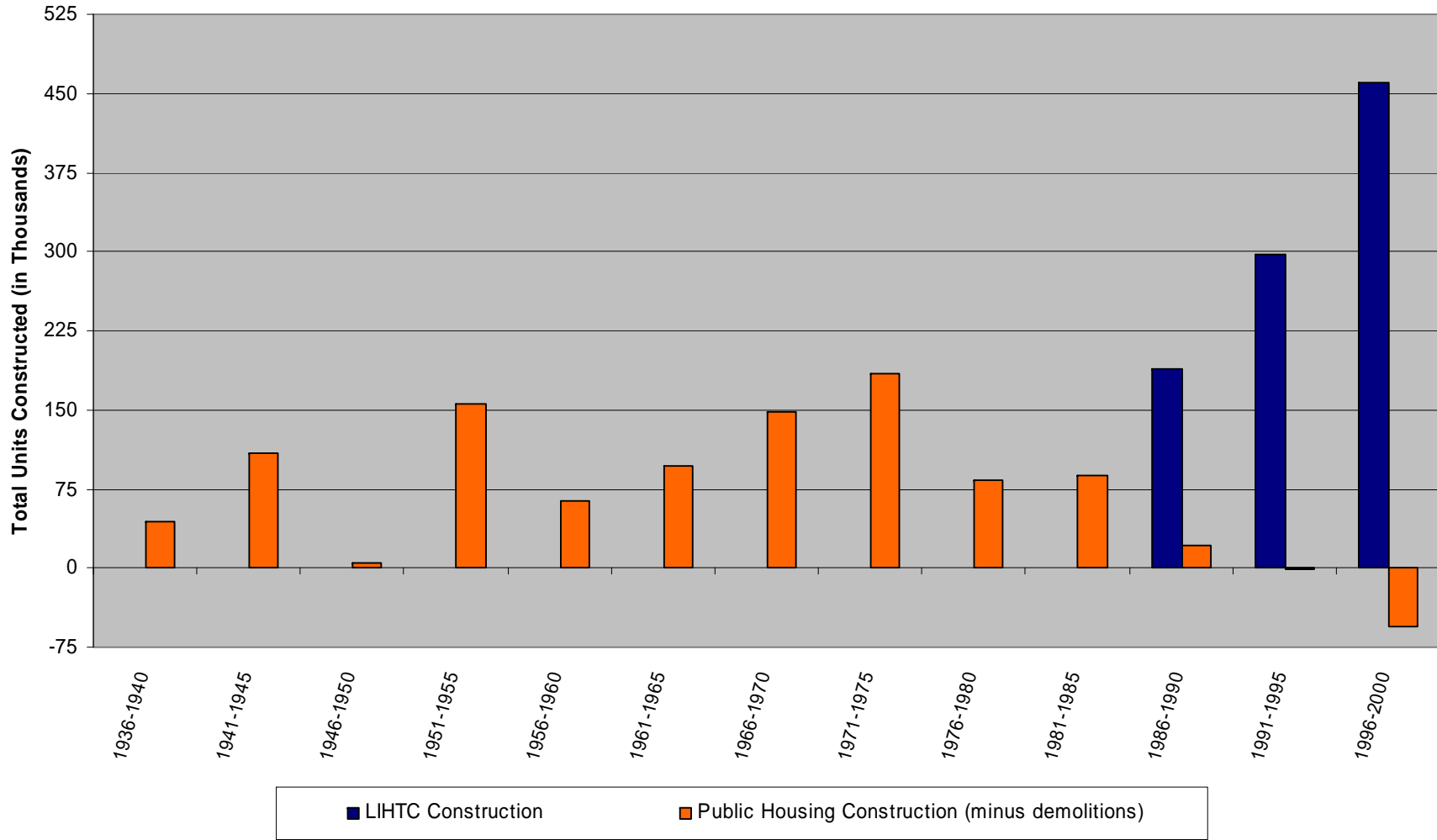


Figure 2a. Location of Low-Income Housing Tax Credit Units by 2000 Neighborhood Income Status

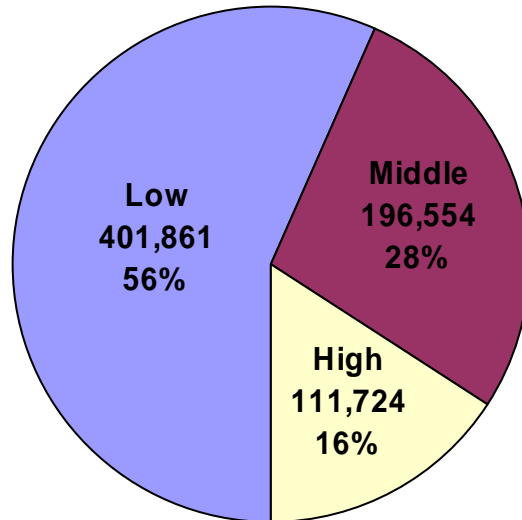


Figure 2b. Location of Traditional Public Housing Units by 2000 Neighborhood Income Status

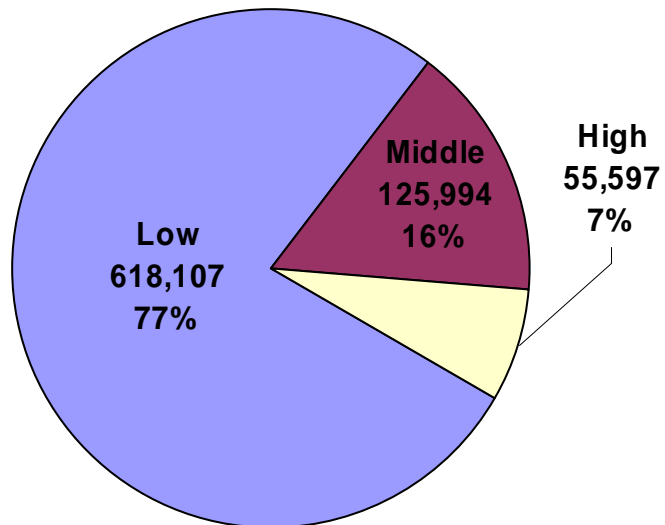


Figure 3a: Crowd Out of Rental Housing With Elastic Demand

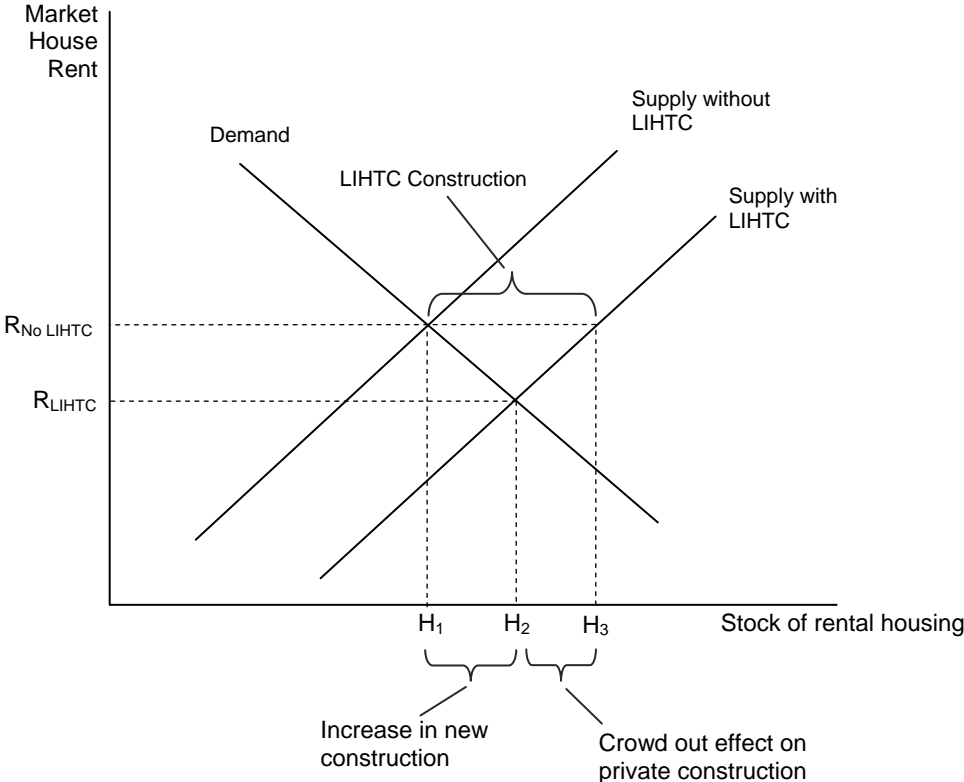


Figure 3b: Crowd Out of Rental Housing With Inelastic Demand

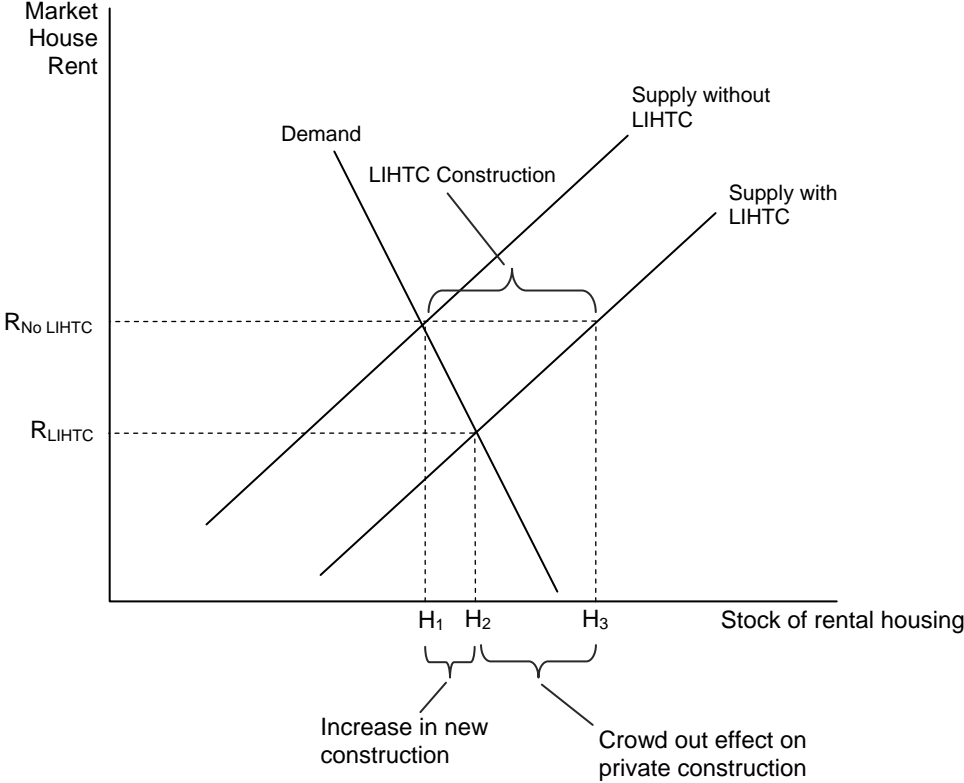


Table 1. National LIHTC Summary Statistics^a

	Total Annual Allocations (\$)^b	Number of Subsidized Units^c
1987	980,533,493	34,491
1988	3,140,987,971	81,408
1989	4,387,952,511	126,200
1990	2,888,647,156	74,029
1991	5,207,469,242	111,970
1992	4,255,013,370	91,300
1993	5,205,992,598	103,756
1994	5,915,192,114	117,099
1995	4,892,206,044	86,343
1996	4,277,723,133	77,003
1997	4,225,625,522	70,453
1998	3,999,808,231	67,822
1999	3,983,473,499	62,240
2000	3,895,882,268	59,601
2001	4,624,992,306	67,261
2002	5,162,994,677	69,310
2003	5,507,541,467	73,877
2004	5,680,347,051	75,600
2005	5,556,042,690	70,630
2006	6,668,538,964	74,278
Total	90,456,964,308	1,594,671

^aData Compiled by the National Council of State Housing Authorities.

^bCalculation made assuming 3 percent inflation and that allocated tax credits would be claimed for the 10 years immediately after allocation.

^cDoes not include unsubsidized, market-rate units sometimes included in LIHTC subsidized properties.

Table 2. Federal Government Low-Income Housing Expenditures (2005-2006)^a
(in Millions of Dollars)

	2005	2006
Internal Revenue Service^b		
Low-Income Housing Tax Credit	4,700	4,900
Preferential Depreciation Allowance	3,800	4,200
State-issued Tax Exempt Financing for Rental Housing	300	300
Department of Housing and Urban Development^c		
Housing Choice Vouchers (HCV)	20,064	20,917
Public Housing	5,017	5,734
Other HUD Programs	8,734	4,559
Department of Agriculture^c		
Rural Housing Administration	1,369	1,029
Total	43,984	41,639

^aLIHTC costs reflect foregone tax revenues associated with the 10-years of tax credit allocations. Those costs are expected to increase sharply in the next several years given an increase in LIHTC allocations since 2001. Public housing operating costs are likely to decline in coming years as increasing numbers of public housing units are demolished.

^bTax Expenditures as Estimated by Joint Committee on Taxation (2005).

^cBudget of the United States, Office of Management and Budget (2006).

Table 3. Sample Means of Regression Variables

	Circles with Radius of _____ Drawn Around Census Tract Centroids			
	County-Level	1 mile	5 mile	10 mile
Private Construction of Rental Housing 1990 - 2000	944.0	405.2	3461.8	9371.8
LIHTC Construction 1990 - 2000	187.2	100.5	867.9	2158.6
# of Rental Units Constructed 1980-1989	1704.8	834.9	7116.1	19027.8
# of Rental Units Constructed 1970-1979	1828.5	956.8	8360.2	22174.7
# of Rental Units Constructed Prior to 1970	4798.4	3769.2	37006.9	96303.6
# of Owner-Occupied Units Constructed 1980-1989	3085.2	865.9	6812.7	19160.1
# of Owner-Occupied Units Constructed 1970-1979	3363.2	960.5	7737.5	21629.0
# of Owner-Occupied Units Constructed Prior to 1970	9604.7	4435.7	41231.2	111190.7
Vacant Rental Units in 1990	816.1	456.1	4086.5	10524.7
Vacant Owner-Occupied Units in 1990	324.3	129.3	1135.1	3059.7
Change in Population 1990 to 2000 (Δ Pop)	8429.2	4276.8	38597.9	102821.9
Change in Median Inc 1990 to 2000 (Δ Inc)	111.1	27.5	224.9	577.59
Observations	3,052	50,256	50,117	49,794

**Table 4: LIHTC Crowd Out of Private Rental Construction
1990 to 2000 at the County-Level**
(Absolute value of t-ratios in parentheses)

	OLS	IV With Population Share	IV With “Cronyism”	IV With Population Share and “Cronyism”
LIHTC Construction 1990-2000	-0.0513 (0.16)	-1.2886 (1.58)	-0.7911 (1.11)	-0.9811 (1.78)
<u>Rental Stock in 1990</u>				
<i>Constructed 1980-1989</i>	0.3018 (3.23)	0.3373 (3.31)	0.3230 (3.36)	0.3285 (3.38)
<i>Constructed 1970-1979</i>	0.0053 (0.08)	0.0713 (0.83)	0.0448 (0.59)	0.0549 (0.74)
<i>Constructed Prior to 1970</i>	0.0016 (0.12)	-0.0047 (0.29)	-0.0022 (0.15)	-0.0032 (0.21)
<u>Owner-Occupied Stock in 1990</u>				
<i>Constructed 1980-1989</i>	0.0690 (1.16)	0.0867 (1.46)	0.0796 (1.39)	0.0823 (1.44)
<i>Constructed 1970-1979</i>	-0.0838 (1.46)	-0.1400 (1.68)	-0.1174 (1.69)	-0.1260 (1.78)
<i>Constructed Prior to 1970</i>	-0.0288 (2.11)	-0.0325 (2.08)	-0.0310 (2.11)	-0.0316 (2.12)
Vacant Rental Units in 1990 (Vac)	-0.1581 (1.24)	0.0433 (0.20)	-0.0377 (0.22)	-0.0067 (0.04)
Change in Population 1990 to 2000 (Δ Pop)	0.0804 (3.19)	0.0803 (3.19)	0.0804 (3.20)	0.0803 (3.20)
Change in Median Inc 1990 to 2000 (Δ Inc)	2.3844 (1.60)	2.8118 (1.51)	2.6400 (1.60)	2.7056 (1.58)
Vac* Δ Pop	-5.82E-07 (2.10)	-9.22E-07 (2.84)	-7.85E-07 (2.22)	-8.37E-07 (2.66)
Vac* Δ Inc	5.12E-06 (0.36)	20.1E-06 (1.41)	14.4E-06 (0.84)	16.8E-06 (1.12)
Density (Pop/Sq mile)	-0.0172 (0.24)	0.0577 (0.61)	0.0276 (0.30)	0.0391 (0.44)
Observations	3,052	3,052	3,052	3,052
Fixed Effects	MSA/StRural	MSA/StRural	MSA/StRural	MSA/StRural
Cluster	MSA/StRural	MSA/StRural	MSA/StRural	MSA/StRural
First Stage: StateAlloc*CntyPopShare	-	0.9428 (4.49)	-	0.7219 (3.82)
First Stage: StateAlloc*CntyPopShare*CntyWin	-	-	0.6534 (5.17)	0.55881 (4.26)
Kleibergen-Paap F-Statistic	-	20.04	25.83	18.76
Hansen-J OverID P-Value	-	-	-	0.6208
R-squared	0.9038	0.888	0.8981	0.8948
Root MSE	841.38	907.78	865.70	879.49

**Table 5: OLS Estimates of LIHTC Crowd Out of Private Rental Construction
1990 to 2000 For Different Circle Radius Areas**
(Absolute value of t-ratios in parentheses)

	1 Mile	2 Mile	3 Mile	4 Mile	5 Mile	10 Mile
LIHTC Construction 1990-2000	-0.4641 (4.73)	-0.4904 (4.12)	-0.5171 (4.23)	-0.5215 (3.93)	-0.5238 (3.38)	-0.1995 (1.10)
<u>Rental Stock in 1990</u>						
<i>Constructed 1980-1989</i>	0.3521 (11.08)	0.3648 (9.06)	0.3632 (7.60)	0.3603 (7.14)	0.3613 (6.64)	0.3912 (6.55)
<i>Constructed 1970-1979</i>	0.0030 (0.16)	-0.0097 (0.42)	-0.0090 (0.32)	-0.0110 (0.34)	-0.0083 (0.23)	0.0016 (0.03)
<i>Constructed Prior to 1970</i>	0.0121 (3.24)	0.0177 (4.48)	0.0166 (3.39)	0.0144 (2.39)	0.0129 (1.96)	0.0045 (0.83)
<u>Owner-Occupied Stock in 1990</u>						
<i>Constructed 1980-1989</i>	0.0934 (7.69)	0.1133 (5.98)	0.1309 (5.12)	0.1491 (4.94)	0.1572 (4.89)	0.1557 (4.83)
<i>Constructed 1970-1979</i>	-0.0524 (4.64)	-0.0671 (4.05)	-0.0807 (3.51)	-0.0946 (3.31)	-0.1051 (3.10)	-0.1050 (2.97)
<i>Constructed Prior to 1970</i>	-0.0213 (5.10)	-0.0246 (5.78)	-0.0210 (4.23)	-0.0168 (3.21)	-0.0137 (2.72)	-0.0143 (2.76)
Vacant Rental Units in 1990 (Vac)	0.0161 (0.36)	0.0189 (0.32)	0.0339 (0.53)	0.0281 (0.42)	0.0092 (0.12)	-0.0223 (0.26)
Change in Population 1990 to 2000 (Δ Pop)	0.0041 (0.69)	0.0110 (1.68)	0.0118 (1.60)	0.0123 (1.58)	0.0151 (1.79)	0.0219 (1.39)
Change in Median Inc 1990 to 2000 (Δ Inc)	2.1539 (4.12)	1.7463 (3.45)	1.5007 (3.11)	1.3828 (3.40)	1.2212 (3.64)	0.9275 (3.68)
Vac* Δ Pop	-33.5E-07 (1.58)	-19.7E-07 (2.11)	-7.02E-07 (1.27)	0.337E-07 (0.09)	1.99E-07 (0.71)	0.825E-07 (0.79)
Vac* Δ Inc	-43.2E-05 (2.55)	-15.2E-05 (1.84)	-9.02E-05 (1.89)	-6.68E-05 (2.66)	-4.39E-05 (3.08)	-1.49E-05 (3.65)
Distance to City Center	-3.4833 (3.69)	-7.6801 (3.37)	-11.5348 (3.18)	-14.5494 (2.98)	-15.9798 (2.63)	-8.9016 (0.68)
Observations	50,256	50,085	50,154	50,150	50,117	49,794
Fixed Effects	County	County	County	County	County	County
Cluster	County	County	County	County	County	County
R-squared	0.4374	0.5440	0.6179	0.6789	0.7326	0.8551
Root MSE	383.04	638.14	868.16	1077.72	1271.93	1972.67

**Table 6: 2SLS Estimates of LIHTC Crowd Out of Private Rental Construction
1990 to 2000 For Different Circle Radius Areas**
(Absolute value of t-ratios in parentheses)

Attributes as of the Year 2000	1 Mile	2 Mile	3 Mile	4 Mile	5 Mile	10 Mile
LIHTC Construction 1990-2000	-0.5643 (2.24)	-0.5050 (1.88)	-0.4502 (1.39)	-0.4626 (1.20)	-0.5864 (1.38)	-1.0692 (2.31)
<u>Rental Stock in 1990</u>						
<i>Constructed 1980-1989</i>	0.3517 (11.06)	0.3646 (9.15)	0.3645 (7.62)	0.3620 (7.17)	0.3593 (6.93)	0.3499 (6.67)
<i>Constructed 1970-1979</i>	0.0068 (0.36)	-0.0091 (0.40)	-0.0117 (0.42)	-0.0129 (0.41)	-0.0073 (0.21)	0.0197 (0.41)
<i>Constructed Prior to 1970</i>	0.0120 (3.09)	0.0177 (4.40)	0.0165 (3.60)	0.0142 (2.79)	0.0134 (2.53)	0.0091 (1.62)
<u>Owner-Occupied Stock in 1990</u>						
<i>Constructed 1980-1989</i>	0.0930 (7.70)	0.1134 (5.84)	0.1299 (4.75)	0.1477 (4.39)	0.1585 (4.52)	0.1816 (4.88)
<i>Constructed 1970-1979</i>	-0.0545 (4.14)	-0.0676 (3.34)	-0.0784 (2.84)	-0.0929 (2.77)	-0.1063 (2.90)	-0.1290 (3.24)
<i>Constructed Prior to 1970</i>	-0.0228 (4.68)	-0.0248 (5.00)	-0.0202 (4.14)	-0.0164 (3.49)	-0.0142 (3.36)	-0.0149 (3.12)
Vacant Rental Units in 1990 (Vac)	0.0327 (0.55)	0.0216 (0.27)	0.0216 (0.22)	0.0180 (0.17)	0.0203 (0.19)	0.1184 (1.21)
Change in Population 1990 to 2000 (Δ Pop)	0.0049 (0.80)	0.0111 (1.67)	0.0115 (1.54)	0.0120 (1.54)	0.0154 (1.83)	0.0267 (1.59)
Change in Median Inc 1990 to 2000 (Δ Inc)	2.2127 (4.20)	1.7554 (3.29)	1.4637 (2.80)	1.3634 (3.10)	1.2369 (3.53)	0.9976 (3.84)
Vac* Δ Pop	-34.8E-07 (1.65)	-19.7E-07 (2.12)	-6.94E-07 (1.23)	0.416E-07 (0.12)	1.85E-07 (0.72)	0.284E-07 (0.26)
Vac* Δ Inc	-43.6E-05 (2.56)	-15.3E-05 (1.80)	-8.82E-05 (1.73)	-6.61E-05 (2.47)	-4.44E-05 (3.02)	-1.53E-05 (3.71)
Distance to City Center	-3.5245 (3.77)	-7.6929 (3.44)	-11.4740 (3.22)	-14.5338 (2.99)	-15.9666 (2.61)	-10.1778 (0.71)
Observations	50,256	50,085	50,154	50,150	50,117	49,794
Fixed Effects	County	County	County	County	County	County
Cluster	County	County	County	County	County	County
First Stage: StateAlloc*CirclePopShare	1.1125 (4.68)	1.0372 (2.84)	0.9467 (2.82)	0.7373 (2.60)	0.6557 (2.71)	0.4570 (1.95)
First Stage: StateAlloc*CircleShare*CntyWin	0.7596 (3.65)	1.0749 (3.65)	1.0316 (3.87)	0.8763 (4.05)	0.6717 (3.69)	0.3521 (1.84)
Kleibergen-Paap F-Statistic	24.97	26.16	28.85	28.15	23.99	11.24
Hansen-J OverID P-Value	0.5579	0.9080	0.5447	0.4294	0.3184	0.1283
R-squared	0.4362	0.5440	0.6175	0.6787	0.7324	0.8418
Root MSE	383.44	638.16	868.58	1078.08	1272.34	2060.86

**Table 7: OLS and 2SLS Estimates of LIHTC Crowd Out of Private Rental Construction
1990 to 2000 For Different Circle Radius Areas**
(Absolute value of t-ratios in parentheses)^a

	1 Mile	2 Mile	3 Mile	4 Mile	5 Mile	10 Mile
OLS	-0.4641 (4.73)	-0.4904 (4.12)	-0.5171 (4.23)	-0.5215 (3.93)	-0.5238 (3.38)	-0.1995 (1.10)
2SLS	-0.5643 (2.24)	-0.5050 (1.88)	-0.4502 (1.39)	-0.4626 (1.20)	-0.5864 (1.38)	-1.0692 (2.31)
Observations	50,256	50,085	50,154	50,150	50,117	49,794
Fixed Effects	County	County	County	County	County	County
Cluster	County	County	County	County	County	County
IV First Stage: StateAlloc*CirclePopShare	1.1125 (4.68)	1.0372 (2.84)	0.9467 (2.82)	0.7373 (2.60)	0.6557 (2.71)	0.4570 (1.95)
IV First Stage: StateAlloc*CirclePopShare*CntyWin	0.7596 (3.65)	1.0749 (3.65)	1.0316 (3.87)	0.8763 (4.05)	0.6717 (3.69)	0.3521 (1.84)
IV: Kleibergen-Paap F-Statistic	24.97	26.16	28.85	28.15	23.99	11.24
IV: Hansen-J OverID P-Value	0.5579	0.9080	0.5447	0.4294	0.3184	0.1283
IV: R-squared	0.4362	0.5440	0.6175	0.6787	0.7324	0.8418
IV: Root MSE	383.44	638.16	868.58	1078.08	1272.34	2060.86

^aOnly the LIHTC coefficients are presented to conserve space. Estimates are taken from Tables 5 and 6.

**Table 8: OLS and 2SLS Estimates of LIHTC Crowd Out of Owner-Occupied Construction
1990 to 2000 For Different Circle Radius Areas**
(Absolute value of t-ratios in parentheses)^a

	1 Mile	2 Mile	3 Mile	4 Mile	5 Mile	10 Mile
OLS	0.2277 (3.51)	0.2482 (2.59)	0.2443 (2.27)	0.2259 (1.76)	0.1949 (1.16)	0.4922 (1.90)
2SLS	0.0935 (0.17)	-0.0060 (0.02)	-0.0010 (0.01)	-0.0789 (0.18)	-0.3071 (0.70)	-0.6877 (0.80)
Observations	50,256	50,085	50,154	50,150	50,117	49,794
Fixed Effects	County	County	County	County	County	County
Cluster	County	County	County	County	County	County
IV First Stage: StateAlloc*CirclePopShare	1.0692 (5.02)	0.8519 (2.58)	0.7513 (2.30)	0.7642 (2.66)	0.8688 (3.56)	0.7287 (3.24)
IV First Stage: StateAlloc*CirclePopShare*CntyWin	0.6270 (3.06)	0.9386 (3.55)	0.8878 (3.67)	0.7692 (3.51)	0.6077 (3.18)	0.2291 (1.41)
IV: Kleibergen-Paap F-Statistic	22.29	20.65	24.70	20.82	19.50	9.77
IV: Hansen-J OverID P-Value	0.6880	0.4639	0.4416	0.4949	0.8834	0.0412
IV: R-squared	0.4224	0.4943	0.5490	0.5854	0.6108	0.6765
IV: Root MSE	708.49	1202.45	1655.26	2072.39	2468.65	4055.56

^aOnly the LIHTC coefficients are presented to conserve space. All variables included in the models in Tables 5 and 6 were included in these models as well. The exception is that rental vacancies were replaced with counts of 1990 vacancies among owner-occupied units, with corresponding adjustments made to the vacancy interactive terms.