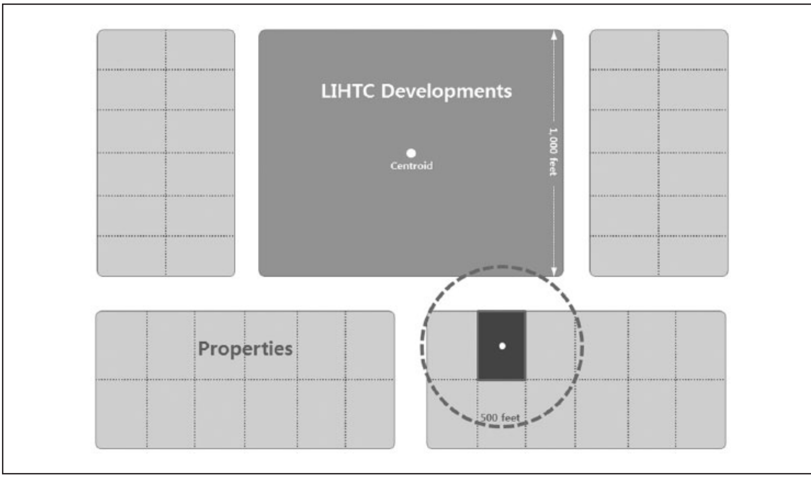

Figure 1. Definition of microneighborhoods.
Note. LIHTC = Low-Income Housing Tax Credit.

Midwest, respectively. Previous research has focused largely on northeastern cities with a legacy of public housing programs such as New York, Philadelphia, and Baltimore (Freeman and Botein 2002; Nguyen 2005). Thus, the findings of this article contribute to extending research on subsidized housing beyond the Northeast region, although the results may not be representative of all areas in the United States.

Charlotte is the 17th largest city in the United States (population 731,000 in 2010) and has experienced steady population growth for several decades (Delmelle et al. 2013). Although many cities in the state have suffered from the current economic recession, Charlotte remains one of the fastest growing cities (Rohe, Donegan, and Han 2012). In contrast, Cleveland has struggled with population decline and neighborhood destabilization for many years due to deindustrialization (Koschinsky 2009). Since its peak in the 1950s, the population of Cleveland has declined steeply from 914,000 to 397,000 in 2010. Mirroring this demographic decline of the city, housing market conditions also remain depressed.

Figure 2 shows the trend in housing sales transactions per person in Charlotte and Cleveland from 1996 to 2007. In the Charlotte housing market, the number of housing sales transactions per person increased gradually during this period (from 0.05 to 0.10). In contrast, the Cleveland housing market fluctuated with fewer transactions per person compared with Charlotte. The annual average number of housing sales transactions per person in Cleveland

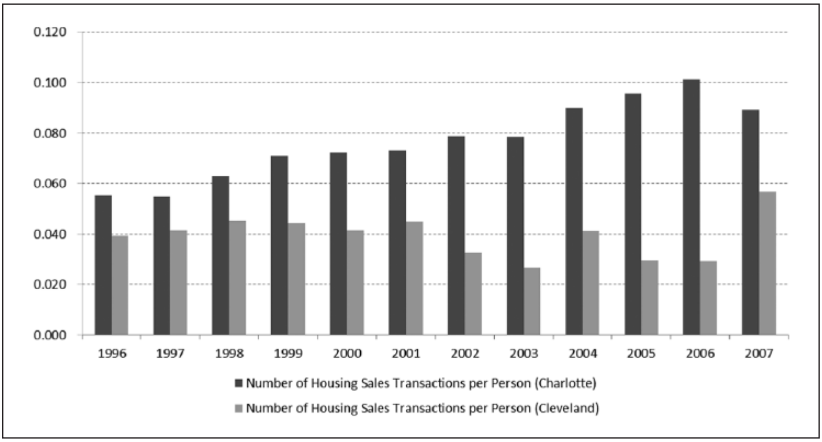

Figure 2. Housing market trends in the cities of Charlotte and Cleveland.

between 1996 and 2007 was 0.04, whereas that in Charlotte was 0.08. Hence, these findings may explain the varying impacts of subsidized housing developments between cities with contrasting housing market conditions.

Data Sources and Descriptions

This study assessed the impact of LIHTC subsidized housing based on historic housing sales data from 1996 to 2007 for the cities of Charlotte and Cleveland. The unit of analysis for this research was a single-family housing unit. Data for housing turnover and sales price for Charlotte were drawn from the Mecklenburg County Assessor's Office; similar data for Cleveland were obtained from the Northeast Ohio Community and Neighborhood Data for Organizing (NEO CANDO), a publicly available database provided by the Center on Urban Poverty and Community Development at Case Western Reserve University. We excluded all forced sales transactions in both cities.[5] Also, low and high outliers in sales price and housing duration were excluded.[6] Census tracts with fewer than 10 property sales were excluded from the analysis. As a result, our final sample included 59,882 housing transactions in Charlotte and 20,824 housing transactions in Cleveland between 1996 and 2007. Among these housing transactions, 40.1% (23,974 properties) in Charlotte and 57.6% (11,989 properties) in Cleveland were not sold during the research period. In addition, in our final sample, 7.9% (4,702 properties) were within 2,000 feet of the Charlotte LIHTC projects and 35.1% (7,309 properties) were within 2,000 feet of the Cleveland LIHTC projects.

The Picture of Subsidized Households data were obtained from the U.S. Department of Housing and Urban Development (HUD) to determine the characteristics of LIHTC developments such as the size of the subsidized housing and their spatial locations in the research areas. However, the location information in these data contained many errors. The longitude and latitude coordinates in these data did not allow for pinpointing the exact location of LIHTC developments. Hence, the location information was not precise enough to analyze the impacts of LIHTC developments at the parcel level because of the differences between the LIHTC locations in the data and actual locations. These data also do not include the project completion dates needed to determine the duration of each property's transaction before and after the LIHTC projects were developed. Thus, we improved the information in these data by using additional data obtained from the Mecklenburg County Integrated Data Store (IDS) Public Reports, the Mecklenburg County GeoPortal,[7] and the Ohio Housing Finance Agency. For Charlotte, we reconfirmed all LIHTC projects and their locations by using the Mecklenburg County GeoPortal, Google satellite imagery, and FindTheData.[8] We also determined the project completion dates through the Mecklenburg County IDS Public Reports. For Cleveland, the LIHTC data set derived from the Ohio Housing Finance Agency includes information about locations and placed in service (PIS) dates. However, we also reconfirmed all of these LIHTC projects and their locations by using Google satellite imagery and FindTheData. As a result, there were 75 projects (4,718 units) in Charlotte and 123 projects (8,603 units) in Cleveland (see Figure 3).

For each city, we conducted empirical analyses for three types of neighborhoods stratified by family income. The 2000 census data for median family income were used for measuring income heterogeneity based on census tract boundaries. Census tracts where the median family income was less than 80% of the city's median family income were defined as low-income neighborhoods; median family income of 80% to 120% of the city's median family income, according to census tracts, were defined as middle-income neighborhoods; and census tracts with a median family income higher than 120% of the city's median family income were defined as high-income neighborhoods.[9]

As seen in Figure 4, the spatial distribution of neighborhoods stratified by family income varies between Charlotte and Cleveland. In Charlotte, high-income neighborhoods are concentrated in a large swath radiating south from the city center, while low- and middle-income neighborhoods form a crescent shape around the city center. Cleveland shows a different pattern of neighborhoods by income, with low-income neighborhoods concentrated in the center of the city whereas high-income neighborhoods are scattered along the fringes of the city.

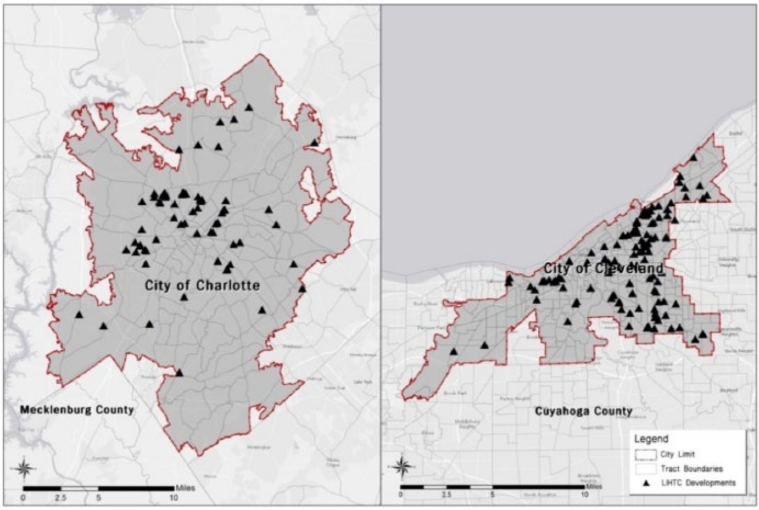

Figure 3. LIHTC developments in research areas.
Note. LIHTC = Low-Income Housing Tax Credit.

Table 1 presents an uneven distribution of LIHTC developments in both cities. Most LIHTC projects were developed in low- and middle-income neighborhoods. A total of 79% of LIHTC projects and 73% of LIHTC units were located in low-income neighborhoods in Charlotte. Similarly, 48% of projects and 59% of units were sited in low-income neighborhoods in Cleveland.

The 2000 census data were used for capturing the unobserved and time-invariant neighborhood characteristics. Our sample included 124 census tracts for Charlotte and 174 census tracts for Cleveland.[10] The geographic coordinates of each property normalized by the distance to the Central Business District (CBD) were calculated from the Mecklenburg and Cuyahoga County parcel data, the 2000 census data, and the Census Transportation Planning Products (CTPP) 2000 Home-to-Work Flows data.[11]

Method

We used the extended Cox hazard model, which is a partial likelihood estimation method, to explore the impact of subsidized housing programs on neighborhood housing turnover. The Cox hazard model first proposed by Cox

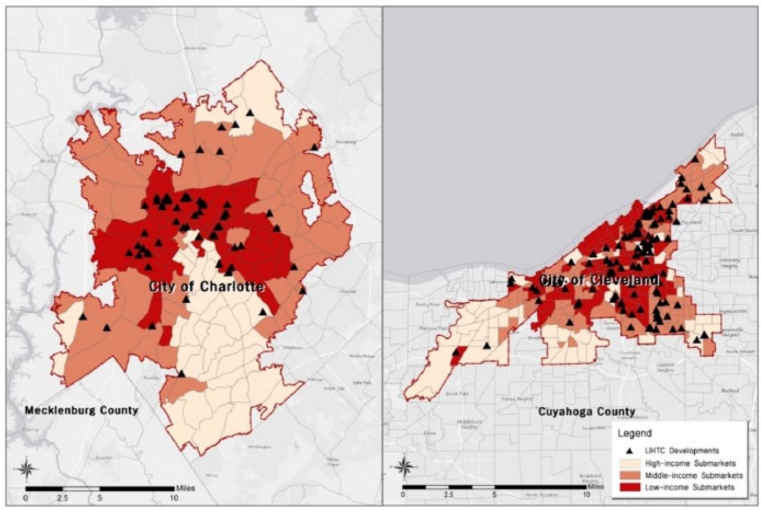

Figure 4. LIHTC developments by neighborhood heterogeneity.
Note. LIHTC = Low-Income Housing Tax Credit.

Table 1. Spatial Distribution of LIHTC Developments by Submarkets.

	Charlotte		Cleveland	
Submarkets (by Income)	No. (%) of Projects	No. (%) of Units	No. (%) of Projects	No. (%) of Units
Low-income	59 (78.67)	3,447 (73.06)	59 (47.97)	5,105 (59.34)
Middle-income	12 (16.00)	830 (17.59)	46 (37.40)	2,645 (30.75)
High-income	4 (5.33)	441 (9.35)	18 (14.63)	853 (9.91)
Citywide	75 (100.00)	4,718 (100.00)	123 (100.00)	8,603 (100.00)

Note. LIHTC = Low-Income Housing Tax Credit.

(1972) has been widely used to explore the time to the hazard occurrence; specifically, this model analyzes the relationship between the survivor of the hazard and various independent variables in duration data (Allison 1984; Heckman and Singer 1984). Housing sales were regarded as the hazard occurrence, and then the housing duration was specified as the duration between the first sale and the next sale (Kim and Horner 2003). The hazard model controls for both of these factors simultaneously and this is a significant advantage of employing the hazard analysis; using ordinary least squares (OLS) or logistic regression would result in the loss of observations as we cannot use dichotomous data for sales occurrence in the OLS regression, and cannot use housing duration in the logistic regression (Vittinghoff et al. 2005). The hazard model also allows the equation to assume time dependence without having to specify time; additionally, it controls both time-varying independent variables and time-invariant independent variables (Vittinghoff et al. 2005). Another advantage of this approach is that after explicitly specifying the risk period, this model can handle certain types of censored observations, especially right-censored observations (Allison 1984; Yamaguchi 1991).[12]

We also clarified the direction of causality to capture the differentials in levels of pre- and post-neighborhood stability associated with subsidized housing developments by comparing control and impact sales (Galster, Tatian, and Smith 1999; Koschinsky 2009; Schwartz et al. 2006). As a result, the extended Cox hazard framework considering time-varying key variables, which are the change of situation (newly developed) of subsidized housing over time, could be specified as

$$h_{int} = h_0(t)\exp\left[\alpha\mathbf{P}_i + \beta\mathbf{L}_i + \gamma\mathbf{N}_n + \theta\mathbf{R}_{it} + \lambda\mathbf{S}_{it}\right], \tag{1}$$

where h_{int} is the hazard rates that are a log-linear function of parameters for the effects of covariates for each property i at time t, and $h_0(t)$ is the baseline hazard function. Each vector, $\mathbf{P}_i$, $\mathbf{L}_i$, and $\mathbf{N}_n$, which does not depend on time, and $\mathbf{R}_{it}$, which depends on time, and their coefficients are the parameters to be estimated. To be specific, $\mathbf{P}_i$ is a vector of the housing price ratio of property i. The variable $\mathbf{L}_i$ includes the dummy variables of locational characteristics for each property such as proximity to parks (within 250 feet), rivers, and lakes (within 500 feet), and the geographic coordinates of each property (normalized by the distance to the CBD) to capture locational attributes (Koschinsky 2009). $\mathbf{N}_n$ is a set of census tract fixed effects capturing the unobserved and time-invariant neighborhood characteristics, which was specified in the Year 2000 census tracts. $\mathbf{R}_{it}$ is a vector of ring variables that capture the differentials of housing turnover before and after subsidized housing was developed within a microneighborhood, described in more detail in the section describing independent variables and the appendix. $\mathbf{S}_{it}$ is a vector of size variables that explores the size effects of newly developed subsidized housing, which is the total number of subsidized housing units within a microneighborhood.

The main interest in the models is to estimate the coefficients θ, which relate to the effects of subsidized housing variables, and these coefficients can be estimated by using the following partial likelihood method:

$$\text{Likelihood}(\theta) = \prod_{i=1}^{l} \left\{ \frac{\exp\left[\sum_k \eta_k X_{ik}(t_i)\right]}{\sum_{j \geq i} \exp\left[\sum_k \eta_k X_{jk}(t_i)\right]} \right\}^{\delta_i}, \tag{2}$$

where $X_{i(j)k}(t)$, which may depend on time, refers to the value of the kth covariate for individual property $i(j)$ at time t, and δ_i refers to a dummy variable that takes the value of 1 when the ith property had an event (hazard) and 0 if the ith property was censored.

For each city, models were estimated separately for three types of neighborhoods stratified by family income, to test whether impacts of subsidized housing vary based on income heterogeneity.

Dependent Variable

Our sample is considered as a flow sample because data on housing transactions were collected over a 12-year time period from 1996 to 2007 (Kim and Horner 2003). The dependent variable in our model was the time to the hazard occurrence. If we regard housing sales as the hazard occurrence, the duration of sales nonoccurrence prior to the hazard can be defined as the housing duration. The housing duration was calculated as the duration of each property's transaction measured in days between the first sale and the next sale during the research period. If there was no next transaction for a given property during the research period, these observations were treated as a right-censored data in our models. Specifically, right-censored observations were properties that had second sales after 2007.

One way to describe the hazard data set is to plot the Kaplan-Meier (K-M) survivor functions, which is an empirical plot showing the probabilities of surviving the hazard of selling a property for each unit of time (Kaplan and Meier 1958):

$$S(t) = \prod_t \left[\left(\frac{n_t - d_t}{n_t}\right)\right], \tag{3}$$

where n_t represents the number of observations that have not failed (not sold) at the beginning of time period t, and d_t denotes the number of failures

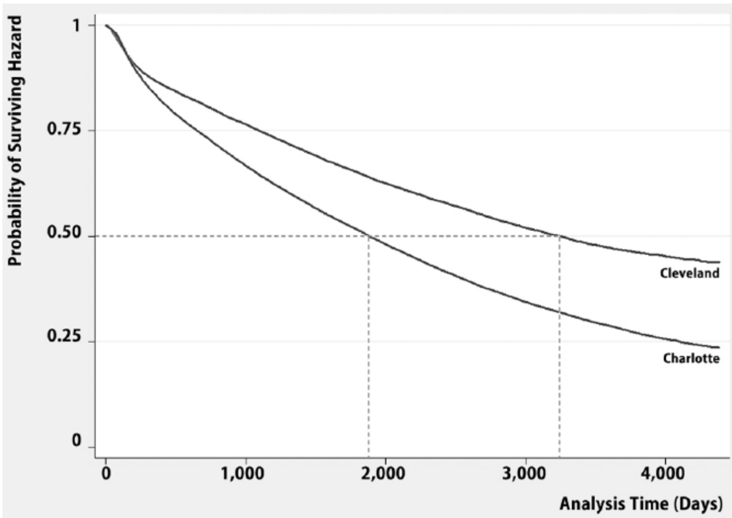

Figure 5. Probability of surviving the hazard of housing turnover.

(the number of housing sales) that have occurred in these observations during time period *t*. The K-M estimator of surviving beyond time *t* (i.e., not having a sales occurrence before time *t*) is the product of survival probabilities in *t* (Poston 2002).

Figure 5 shows the probabilities of surviving the hazard of housing turnover over time (measured in days) in Charlotte and Cleveland. The K-M survivor curve for Charlotte drops more sharply than that for Cleveland. The probability of surviving the hazard of housing turnover drops from 1.0 to 0.5 by approximately the 1,800th day (5th year) in Charlotte, while the same drop in probability for Cleveland is reached by the 3,300th day (9th year). Thus, there were clear differences for housing turnover rates between two cities in our sample; properties in Charlotte tend to turn over faster than those in Cleveland.

Independent Variables

Independent variables for empirical models included housing, locational, neighborhoods, and LIHTC development characteristics of each property. We used the housing sales price to control for housing characteristics.[13] For the housing price variable, we used housing price ratios ($\mathbf{P}_i$) instead of exact price values to deal with the time-dependent nature of monetary variables (Kim and Horner 2003). To remove time dependency from housing prices, the housing sales price of the ith property in the kth year is standardized by the city's average housing price in the kth year, $\overline{p_j}$. It could be specified as

$$\overline{x_i} = \frac{p_{ik}}{\overline{p_j}}. \tag{4}$$

We employed spatial fixed effects to control for the locational ($\mathbf{L}_i$) and neighborhood ($\mathbf{N}_n$) characteristics of each property. Specifically, this study used census tract dummy variables signifying the census identification number for each neighborhood to control for their distinct characteristics. The geographic coordinates of each property normalized by the distance to the CBD were included to account for the locational characteristics of each property. Specifically, we defined a CBD as the centroid of the census tract with the highest job density in the city. Job density was calculated as the number of jobs per square meter of land use in each census tract.[14] Also, indicators for the proximity to parks, rivers, and lakes in Charlotte and Cleveland were used to capture any remaining locational characteristics.

The key variables comprise the vector of ring variables ($\mathbf{R}_{it}$), which capture the differentials in levels of pre- and post-housing turnover ratios relating to the subsidized housing developments by comparing control and impact sales (Galster 2004; Koschinsky 2009; S. S. Lee 2008). Differences between impact and control sales are also controlled by spatial fixed effects (Galster 2004). The inherent concept of these variables could be explained in terms of control/impact sales and pre- or post-differentials of the hazard.

First, all sales can be categorized into two groups: control sales and impact sales. Impact sales are defined as housing transactions where subsidized housing is located within the property's microneighborhood. Control sales are transactions where subsidized housing is not within the property's microneighborhood but located in the same census tract with impact sales (Koschinsky 2009). Second, the ring variables measure the differentials in the levels of hazard in microneighborhoods including subsidized housing before and after its completion. Impact sales can be further divided into two categories according to the completion dates of subsidized housing: pre-impact sales and post-impact sales. Pre-impact sales are transactions that occurred prior to the development of subsidized housing whereas post-impact sales are sales that took place after subsidized housing was developed within their microneighborhoods.

The vector of ring variables includes two dummy variables for each of the two microneighborhoods for each property (0–500 and 500–2,000 feet) to capture the differences in hazard ratios. Pre-impact sales take on a value of 1 when there is or will be LIHTC developments within the microneighborhood of the residential property. The pre-impact sales capture the existing average hazard ratios in microneighborhoods before subsidized housing is developed and reflect the inherent neighborhood stability prior to subsidized housing. Post-impact sales take on a value of 1 when the residential property has a completed LIHTC development within the property's microneighborhood. The post-impact sales measure the levels of hazard in microneighborhoods after subsidized housing is developed. Therefore, the vector of ring variables allows us to compare the differentials in levels of housing turnover ratios between impact sales and control sales for each of the two types of microneighborhoods before and after subsidized housing was developed.

Thus, the findings of this study assess the impacts of the LIHTC program on neighborhood stability by constructing multidimensional variables related to the impacts of subsidized housing to clarify the direction of causality.

Results

Citywide Results

Table 2 shows the key coefficients for the citywide models for Charlotte and Cleveland.[15] We first present the results for Charlotte.

For housing property values, the negative hazard coefficients indicate that sale prices of properties are inversely related to housing turnover rates; hence, more expensive properties tend to turn over more slowly on average. A one-unit increase in the annual average price ratio results in a 6.1% lower probability of housing turnover (hazard), keeping all other factors constant.[16] However, this marginal effect, which is the probability of housing turnover, increases by 1.3% as the annual average price ratio increases.

The completion of LIHTC developments in a microneighborhood had a significant spillover effect on neighborhood stability, as indicated by housing turnover, in Charlotte. Before the development of LIHTC projects within the microneighborhoods, the pre-impact variables show a negative hazard coefficient. This indicates that the probability of housing turnover is lower compared with the control area (i.e., outside the impact area but in the same census tract) before the LIHTC projects are sited; it is statistically significant only in the outer ring (500–2,000 feet). Holding all other factors constant, the probability of housing turnover for impact sales was 27.4% less than that for control sales. However, the probability of housing turnover significantly increased after the introduction of LIHTC units into the microneighborhoods. The probability of housing turnover located adjacent and in

Table 2. Citywide Results.

Variables	Citywide Results, Charlotte			Citywide Results, Cleveland		
	Coefficient	z Score	Hazard Ratio	Coefficient	z Score	Hazard Ratio
Sales price (standardized)	−0.063***	−5.17	0.939	−1.639***	−25.28	0.194
Sales price^2 (standardized)	0.013***	10.56	1.013	0.392***	14.33	1.480
Pre-impact 0–500 feet	−0.193	−1.36	0.825	−0.405***	−3.43	0.667
Post-impact 0–500 feet	0.300**	2.01	1.350	0.573***	4.63	1.773
Pre-impact 500–2,000 feet	−0.321***	−5.10	0.726	−0.412***	−7.00	0.662
Post-impact 500–2,000 feet	0.240***	4.14	1.271	0.539***	10.40	1.714
No. of LIHTC units	0.001	1.53	1.001	0.000	−1.52	1.000
X, Y coordinates (CBD)		Yes			Yes	
Census tract fixed effects		Yes			Yes	
No. of observations		59,882			20,824	
Log likelihood		−370,499.27			−81,768.169	
Likelihood ratio χ^2		2,445.99***			3,252.42***	

Note. LIHTC = Low-Income Housing Tax Credit; CBD = Central Business District.
*10% significance level. **5% significance level. ***1% significance level.

proximity to LIHTC developments was 35.0% higher in the inner ring (immediate neighborhood) and 27.1% higher in the outer ring (functional neighborhood) compared with control properties located outside of the microneighborhoods after LIHTC projects were sited. However, the association between the project size of the LIHTC and housing turnover was not statistically significant in Charlotte.

The results for Cleveland tell a similar story to those for Charlotte. The coefficients for property values, like those in Charlotte, show that the probability of housing turnover is nonlinear. However, the magnitude of property values on housing turnover is more substantial than other factors in the Cleveland housing market. For every additional one unit in the annual average price ratio, the probability of housing turnover is reduced by 80.6%, but this marginal effect increases by 48.0% as the annual average price ratio increases. This implies that the housing sales price may be a primary determinant of the in- and out-migration of neighborhood residents in cities with depressed market conditions such as Cleveland.

For Cleveland, the probabilities of housing turnover in the two distance rings before and after LIHTC developments show the same signs as that of Charlotte. The probability of housing turnover was 33.3% lower in the inner ring and 33.8% lower in the outer ring compared with the control areas before the LIHTC was developed. However, after the LIHTC projects are sited in the immediate and functional neighborhoods, the hazards of housing turnover were about 1.8 and 1.7 times greater than they were for those in the control areas, respectively. Thus, the gaps in turnover between impact and control areas that exist before the completion of the LIHTC projects are magnified afterward, from −33.3% to 77.3% within immediate neighborhoods and from −33.8% to 71.4% within functional neighborhoods. This indicates that the completion of the LIHTC developments significantly increased the probability of housing turnover in neighborhoods, particularly within the immediate neighborhood.

Neighborhood Heterogeneity Results

We also examined how impacts of LIHTC developments vary according to housing submarket heterogeneity in terms of income levels. The results for low-, middle-, and high-income neighborhoods in Charlotte and Cleveland suggest a mixed story according to neighborhood heterogeneity and contrasting housing market conditions.

Table 3 shows the results for high-income neighborhoods in Charlotte and Cleveland. For the high-income submarket in Charlotte, it is notable that the hazard of housing turnover increased dramatically within the inner ring after LIHTC was developed. Before the development of LIHTC projects, the probability of turnover was 60.1% lower than for control sales in the immediate neighborhood. After the introduction of subsidized housing, however, the probability of housing turnover was about 2.45 times greater than the control area. In addition, the probability of turnover in functional neighborhoods was 64.4% less than that for control sales, before LIHTC was introduced, and 45.2% higher than control sales after LIHTC was developed. In sum, the spillover effects on housing turnovers were much more substantial at closer proximities to LIHTC units after LIHTC projects were developed. Size effects of LIHTC developments also significantly increased housing turnover, although the magnitude of this impact was not substantial.

The results from the city of Cleveland tell a different story than those of Charlotte. After the LIHTC was developed within immediate neighborhoods, the probability of housing turnover was 92.3% higher than the control area.

Table 3. Results in High-Income Neighborhoods.

	High-Income Submarkets, Charlotte			High-Income Submarkets, Cleveland		
Variables	Coefficient	z Score	Hazard Ratio	Coefficient	z Score	Hazard Ratio
Sales price (standardized)	−0.388***	−22.56	0.679	−1.890***	−15.65	0.151
Sales price^2 (standardized)	0.029***	18.43	1.030	0.432***	10.13	1.541
Pre-impact 0–500 feet	−0.919***	−2.89	0.399	0.102	0.26	1.107
Post-impact 0–500 feet	0.897***	2.71	2.452	0.654*	1.74	1.923
Pre-impact 500–2,000 feet	−1.033***	−5.53	0.356	0.705***	3.39	2.023
Post-impact 500–2,000 feet	0.373***	2.77	1.452	−0.049	−0.32	0.952
No. of LIHTC units	0.004***	4.12	1.004	−0.009***	−4.33	0.991
X, *Y* coordinates (CBD)		Yes			Yes	
Census tract fixed effects		Yes			Yes	
No. of observations		25,226			9,924	
Log likelihood		−142,641.2			−26,781.558	
Likelihood ratio χ^2		1,269.10***			843.61***	

Note. LIHTC = Low-Income Housing Tax Credit; CBD = Central Business District.
*10% significance level. **5% significance level. ***1% significance level.

However, this impact was statistically significant at the 10% level. Interestingly, building more units in LIHTC developments appears to decrease the effects, although the magnitude of this size impact was not substantial; a one-unit increase in the number of LIHTC units at the time of sale resulted in only a 0.9% lower chance of housing turnover, ceteris paribus.

In sum, the results for the high-income submarket show that in Charlotte, high-income residents are sensitive to the influx of LIHTC households into neighborhoods, particularly into the immediate neighborhood. However, the introduction of LIHTC developments only appears to have a significant impact within the immediate neighborhood for the high-income submarket in Cleveland.[17] Size effects of LIHTC developments showed that the project size was directly related to housing turnover rates in Charlotte, while that was inversely related to housing turnover rates in Cleveland.

Table 4. Results in Middle-Income Neighborhoods.

	Middle-Income Submarkets, Charlotte			Middle-Income Submarkets, Cleveland		
Variables	Coefficient	z Score	Hazard Ratio	Coefficient	z Score	Hazard Ratio
Sales price (standardized)	0.296***	15.38	1.345	−1.802***	−16.45	0.165
Sales price² (standardized)	−0.013***	−6.08	0.987	0.425***	7.21	1.530
Pre-impact 0–500 feet	−0.317	−1.17	0.728	−0.659***	−3.68	0.517
Post-impact 0–500 feet	0.510*	1.86	1.665	0.632***	3.30	1.881
Pre-impact 500–2,000 feet	−0.204	−1.28	0.815	−0.577***	−6.86	0.562
Post-impact 500–2,000 feet	0.250***	2.51	1.284	0.612***	8.06	1.844
No. of LIHTC units	0.001	0.42	1.001	0.000	−0.58	1.000
X, Y coordinates (CBD)		Yes			Yes	
Census tract fixed effects		Yes			Yes	
No. of observations		25,052			7,702	
Log likelihood		−144,832.22			−32,127.007	
Likelihood ratio χ^2		1,471.60***			1,152.49***	

Note. LIHTC = Low-Income Housing Tax Credit; CBD = Central Business District.
*10% significance level. **5% significance level. ***1% significance level.

In the middle-income neighborhoods of Charlotte and Cleveland, the results were generally consistent among key variables (see Table 4). The post-impact variables show that the probability of selling properties was higher after the LIHTC projects were completed in both immediate and functional neighborhoods. The pre-impact variables were not statistically significant for Charlotte, although the coefficients maintained the same signs as other models. In sum, our results show that spillover effects are consistent in the middle-income submarket regardless of differences in housing market conditions (i.e., hot and cold markets).

The results for low-income neighborhoods in Charlotte and Cleveland are presented in Table 5. Similar to the previous models, we can observe that the pre-impact variables showed negative coefficients and the coefficients for the post-impact variables were positive, indicating that the probabilities of housing turnover were lower compared with the control areas before

Table 5. Results in Low-Income Neighborhoods.

	Low-Income Submarkets, Charlotte			Low-Income Submarkets, Cleveland		
Variables	Coefficient	z Score	Hazard Ratio	Coefficient	z Score	Hazard Ratio
Sales price (standardized)	−1.123***	−12.74	0.325	−1.138***	−8.78	0.320
Sales price^2 (standardized)	0.289***	15.28	1.335	0.328***	5.65	1.388
Pre-impact 0–500 feet	−0.160	−0.71	0.852	−0.188	−1.00	0.829
Post-impact 0–500 feet	0.246	1.08	1.279	0.589***	3.25	1.803
Pre-impact 500–2,000 feet	−0.453***	−4.25	0.636	−0.404***	−3.49	0.667
Post-impact 500–2,000 feet	0.438***	4.37	1.550	0.669***	8.01	1.952
No. of LIHTC units	0.000	0.90	1.000	0.000	−0.90	1.000
X, *Y* coordinates (CBD)		Yes			Yes	
Census tract fixed effects		Yes			Yes	
No. of observations		9,604			3,198	
Log likelihood		−46,145.645			−13,523.945	
Likelihood ratio χ^2		849.30***			396.86***	

Note. LIHTC = Low-Income Housing Tax Credit; CBD = Central Business District.
*10% significance level. **5% significance level. ***1% significance level.

LIHTC projects were developed and higher than the control areas after LIHTC developments were introduced. However, the probabilities of housing turnover were statistically significant only in functional neighborhoods of Charlotte. For the low-income neighborhoods of Charlotte, the probability of turnover in functional neighborhoods was 36.4% less than that for the control properties, before LIHTC was developed, and 55.0% higher than control properties after LIHTC was introduced. For the low-income neighborhoods of Cleveland, after the LIHTC projects are developed in the immediate and functional neighborhoods, the probabilities of housing turnover were about 1.8 and 2.0 times greater than properties in the control area, respectively.

Table 6 summarizes our major findings of the probabilities of housing turnover before and after LIHTC was developed in the immediate and

Table 6. Summary of Probabilities of Housing Turnover Before and After LIHTC Developments.

Variables	Probabilities of Turnover, Charlotte		Probabilities of Turnover, Cleveland	
	Pre-LIHTC (%)	Post-LIHTC (%)	Pre-LIHTC (%)	Post-LIHTC (%)
Citywide results				
Immediate neighborhoods (0–500 feet)	—	135.0	66.7	177.3
Functional neighborhoods (500–2,000 feet)	72.6	127.1	66.2	171.4
High-income submarkets				
Immediate neighborhoods (0–500 feet)	39.9	245.2	—	192.3
Functional neighborhoods (500–2,000 feet)	35.6	145.2	202.3	—
Middle-income submarkets				
Immediate neighborhoods (0–500 feet)	—	166.5	51.7	188.1
Functional neighborhoods (500–2,000 feet)	—	128.4	56.2	184.4
Low-income submarkets				
Immediate neighborhoods (0–500 feet)	—	—	—	180.3
Functional neighborhoods (500–2,000 feet)	63.6	155.0	66.7	195.2

Note. LIHTC = Low-Income Housing Tax Credit.

functional neighborhoods for Charlotte and Cleveland. Assessing the results, there was strong evidence that LIHTC developments significantly increased neighborhood housing turnover in both cities. The probability of housing turnover was higher than that of control sales after controlling for preexisting turnover levels prior to LIHTC construction in both cities. There were also consistently significant spillover effects on neighborhood turnover across socioeconomic strata.

Conclusion

Our citywide results suggest that LIHTC developments generated significant spillover effects undermining neighborhood stability in both Charlotte and Cleveland. These results are consistent with those found by Baum-Snow and

Marion (2009). Our findings also indicated that the impacts of LIHTC developments vary across different housing submarkets. The results for high-income submarkets suggested strong negative impacts in immediate neighborhoods, especially in Charlotte. Exceptionally high housing turnover after the completion of LIHTC developments within immediate neighborhoods implies that neighbor attitudes about the influx of LIHTC households would be more sensitive in high-income submarkets. It is also noteworthy that the size effects of LIHTC developments were only significant in the high-income submarkets of both cities. High-income neighbors may be more sensitive to the project size of developments. Building more units in LIHTC projects stimulated rapid housing turnovers in Charlotte, while increases in LIHTC units mitigated spillover effects of LIHTC developments in Cleveland. This finding implies that although LIHTC developments accelerated housing turnover in both cities, larger projects in cities with depressed housing market conditions, such as Cleveland, might mitigate spillover effects of LIHTC developments due to the removal of disamenities such as dilapidated buildings and other eyesores (Schwartz et al. 2006).

Our results for middle-income submarkets showed that spillover effects were significant in both immediate and functional neighborhoods for both cities, with the influx of LIHTC subsidized households stimulating high housing turnovers under both depressed and hot housing market conditions. Interestingly, our findings for the low-income submarkets in Charlotte showed that housing turnovers due to LIHTC completion were only significant within the properties' functional neighborhoods. This finding might lead to several possible conclusions. First, tenant characteristics between subsidized housing and nonsubsidized housing may not be as noticeable in low-income submarkets of Charlotte. Thus, the response to the influx of LIHTC households into immediate neighborhoods might not be as sensitive. Second, low-income neighbors may have less information or lack awareness about the introduction of LIHTC households, due to lower education or income level (Kobie and Lee 2011). Finally, real estate agents may be less willing to provide this information to low-income neighbors and may not want to exert the same level of effort for low-income clients due to differences of commission (Galster 1987; Kobie and Lee 2011).

Increasing rates of housing turnover may indicate neighborhood instability. Rapid turnover may restrict social ties among neighbors, and contribute to the breakdown of informal social control (Ross, Reynolds, and Geis 2000; Sampson 1985; Sampson and Groves 1989). The flow of residents in and out of neighborhoods in response to LIHTC developments might undermine social integration by depriving residents of the opportunities to know each other, share norms, and sustain neighborhood networks. Also, our results raise concerns about high rates of housing turnover in low-income neighborhoods in response to LIHTC developments because the concurrence of high poverty levels and neighborhood instability is associated with lower neighborhood integration and higher levels of violent crime (Smith and Jarjoura 1988). Thus, our findings that subsidized housing tends to be located in distressed neighborhoods stimulate concerns about promoting neighborhood instability. This suggests that existing conditions related to neighborhood stability should be considered when placing LIHTC units in neighborhoods, and these conditions should be monitored in neighborhoods with LIHTC housing.

Additional research is needed to better understand the conditions under which LIHTC developments may hurt or help neighborhood stability. Many researchers suggest that the LIHTC program should do a better job of income mixing (Van Zandt and Mhatre 2009). Although the program was designed to facilitate mixing of incomes, in practice nearly 85% of all units developed through 2002 were low income (HUD, Office of Policy Development and Research 2005). The mixing of incomes within developments may need to be sensitive to the neighborhood context to help overcome concerns about the discrepancies between LIHTC residents and surrounding neighbors. At the very least, cities need to monitor stability within neighborhoods and ensure that increased turnover does not lead to additional destabilization in terms of property maintenance and upkeep. This may include the implementation of programs designed to ease the transition of new residents into the neighborhood.

Our results for Charlotte and Cleveland suggest that the introduction of LIHTC developments may deteriorate neighborhood stability in terms of high rates of homeowner turnover. However, this study was unable to explore renter turnover due to data limitations, although housing turnover in renter-occupied units might be greater in low-income neighborhoods (Crowley 2003). Some researchers also suggest that LIHTC developments crowd out unsubsidized rental housing construction in neighborhoods (Baum-Snow and Marion 2009; Eriksen and Rosenthal 2010). In this context, there is a growing concern about renter turnover when it is linked to the crowd-out effects of LIHTC developments on unsubsidized rental housing construction in neighborhoods. Thus, an additional study for the concurrence of high renter turnover and crowd-out effect in neighborhoods may look beyond the current role of the LIHTC program as a simple expansion of subsidized renter housing units. Future studies should examine the relationships between subsidized housing and housing turnovers classified by household types. However, according to our findings, one can show the change of neighbors in terms of homeowner turnover due to LIHTC developments, regardless of the vulnerability of neighborhood stability between renters and homeowners.

It is also important to note that our study cannot identify the change of socioeconomic characteristics in neighborhoods where LIHTC units are developed, especially in terms of gentrification or filtering down. The socioeconomic changes of neighborhoods, however, might be capitalized into housing prices (Baum-Snow and Marion 2009). In other words, based on high housing turnover, positive impacts of LIHTC developments on neighboring housing prices may be related to the gentrification process indicating the influx of wealthier residents into neighborhoods because the increasing property value displaces many existing residents by making the area unaffordable (Lang 1982). Particularly, high housing turnover in low-income neighborhoods may be part of the gentrification process. Thus, our results of high housing turnover in low-income neighborhoods may be part of the gentrification process if LIHTC developments in low-income neighborhoods result in higher housing prices, and then, the increasing property values are related to high housing turnover. In such cases, LIHTC developments may not necessarily lead to neighborhood instability in the long run. This question exploring the association between LIHTC developments and changes in housing prices is currently analyzed in a separate study by the authors. However, in spite of this limitation, our findings show that LIHTC developments may increase neighborhood housing turnover, regardless of the change of neighborhood stability in the short or long run.

Finally, though our results are robust, we caution that the study may not be generalizable to other U.S. cities. Although we described Charlotte and Cleveland as having hot and depressed housing markets, respectively, these two cities may not be representative of housing market conditions in other cities due to the unique characteristics of each city. We suggest that future studies should further examine the association between neighborhood stability and subsidized housing programs by exploring other cities, other housing market conditions, other types of subsidized programs, and other household types.

Appendix

Cox Hazard Model with Time-Varying Independent Variables—Episode Splitting

If time-varying variables are considered in the Cox proportional hazard model, the proportional hazard assumption is no longer satisfied (Kleinbaum and Klein 2012). However, the Cox hazard model can still be used and is called the extended Cox hazard model (Kleinbaum and Klein 2012). Extended Cox hazard model can easily control time-varying independent variables using episode splitting. In our empirical models, post-impact variables were treated as time-varying covariates because the LIHTC project can be developed with the housing duration between the first sale and the next sale of a property. In this situation, the hazard data set was reorganized to incorporate time-varying covariates using episode splitting (Allison 2004). For instance, consider a property i with two different values for a covariate (X_n: post-impact variable):

$$X_1 = 0 \quad \text{if } t < u$$
$$X_2 = 1 \quad \text{if } t \geq u,$$

where u is the completion date of LIHTC developments, t is the date of sales, and T_i is the survival time.

Table A1. Example of Episode Splitting.

Record No.	Event (Sales Occurrence)	Survival Time	Entry Time	Post-impact Variables
Data record for property *i* (before episode splitting)				
1	1	T_i	0	—
Data record for property *i* (after episode splitting)				
1	0	u	0	X_1 (=0)
2	1	T_i	u	X_2 (=1)

As seen in Table A1, after episode splitting, the survival time (episode) for a property i was split into two subperiods (Jenkins 2005). Also, in the first episode, the post-impact variable takes on the value X_1, and in the second episode, the post-impact variable takes on the value X_2. This transformation of the hazard data set that is episode splitting was used to account for the cases that LIHTC projects were developed between the first sale and the next sale of properties.

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Notes

1. According to the U.S. Department of Housing and Urban Development (HUD) Report in the Low-Income Housing Tax Credit (LIHTC) database, around 24,000 projects including about 1.8 million housing units have been placed in service through this program between 1995 and 2011.
2. O'Regan and Horn (2013) found that around 45% of LIHTC tenants have extremely low incomes in 18 states in 2010 although LIHTC income eligibility limits are required subsidized units to be occupied by households with incomes at 50% or 60% of the Area Median Income (AMI).
3. Housing submarkets could be defined in terms of ethnicity and income level. However, we focused on the income levels of neighborhoods to signify the neighborhood's heterogeneity. Because LIHTC subsidized units are almost always occupied by households below the 60% of AMI, the discrepancies in income levels of tenant characteristics between LIHTC households and neighbors would play a key role in allowing different spillover effects across neighborhoods (Freeman 2004).
4. Different researchers used different criteria to define the radial distance of microneighborhood boundaries. For instance, microneighborhoods' radial distances are defined as 1,000 feet by Koschinsky (2009); 1,500 feet by Castells (2010); and 2,000 feet by Schwartz et al. (2006). In some studies, those radial distances are classified as three distance bands: 500, 1,000, and 2,000 feet (Galster et al. 1999) or 750, 1,500, and 2,500 feet (Lee 2008).
5. In the case of the city of Cleveland, transactions between warranty deeds were selected to clarify arm's length transactions.
6. The top and bottom 1% of the sample in sales prices was excluded to remove extremely low and high prices. The bottom 1% of the sample in housing duration was also excluded.
7. Mecklenburg County GeoPortal provides extensive information, especially in terms of property, environment, community information, and even building images (maps.co.mecklenburg.nc.us).
8. FindTheData allows us to identify the addresses, sizes, types, and building images of LIHTC projects (www.findthedata.org).
9. The HUD's 2000 median family income for the city of Charlotte was $56,500 and for the city of Cleveland was $30,300.
10. In addition, there were 46 census tracts for Charlotte and 51 census tracts for Cleveland in low-income submarkets; there were 41 census tracts for Charlotte and 77 census tracts for Cleveland in middle-income submarkets; and there were 37 census tracts for Charlotte and 46 census tracts for Cleveland in high-income submarkets.
11. In addition, we used the Mecklenburg and Cuyahoga Geographical Information System (GIS) Center data to account for the proximity to parks, rivers, and lakes. In our sample, 6.7% of properties (4,000 properties) were within 250 feet of parks in Charlotte and 4.5% (943 properties) were within 250 feet of parks in Cleveland. Also, 1.2% of properties (250 properties) in Cleveland were within 500 feet of river and lakes.

12. Censoring exists when an observation is not observed entirely during the risk period (1996–2007). When the observation is terminated before the hazard has occurred, this observation is censored on the right at the end of the risk period.
13. We used the housing sales price instead of housing structural characteristics. Housing structure characteristics, such as heated areas, lot size, number of bedrooms, and building age, might be related to housing turnovers. However, the housing price variable captures many of the amenities related to the property itself, especially in terms of housing structure characteristics. Hence, we excluded housing structure characteristics in our model to resolve multicollinearity problems (Kim and Horner 2003).
14. Number of jobs for each census tract was derived from the 2000 Census Transportation Planning Products (CTPP Home-to-Work Flows), and land area for each census tract was derived from the Census 2000 data.
15. Our models included many census tract dummy variables to account for neighborhood characteristics. For instance, census tract fixed effects for Charlotte consisted of 123 indicators and those for Cleveland consisted of 173 indicators. Thus, for brevity, the tables included in this article report only the results of key variables. The full tables including all variables (for locational and neighborhood characteristics) are available from the lead author upon request.
16. If the values of the hazard coefficients are exponentiated, hazard ratios can be obtained. Thus, calculating $100(e^{\beta} - 1)$ indicates the percentage change in the hazard with each one-unit change in independent variables, termed *hazard ratios* (Allison 1984).
17. For the analysis of high-income submarkets, small variation of impact sales in the high-income neighborhoods might be an issue. In Cleveland high-income neighborhoods, of the 9,924 sales, 1.3% (122 sales) and 10.4% (1,034 sales) are within 500 feet and 500 to 2,000 feet of LIHTC projects, respectively. In Charlotte high-income neighborhoods, of the 25,226 sales, 0.3% (72 sales) and 3.2% (815 sales) are within 500 feet and 500 to 2,000 feet of LIHTC projects, respectively.

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