RESEARCH BRIEF

Financing Affordable Housing through the Charlotte Housing Trust Fund: Impact on Housing Stability at the Neighborhood Level

Results from the Data / *Eric Moore, Kerrie Stewart*

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Why This Matters

Charlotte faces a persistent housing crisis driven, in part, by a shortage of affordable housing and rising levels of housing instability, where half of renter households and more than a fifth of owner-occupied households are cost-burdened, i.e., spending over a third of their income on housing.[1] The situation is exacerbated as the cost of rental housing substantially outpaces the average hourly wage for renters.[2]

This research investigates the impact of financing affordable housing through the Housing Trust Fund (HTF) on housing instability at the neighborhood level. To better understand changes in housing instability, the UNC Charlotte Urban Institute research team compared neighborhoods with properties financed by the HTF with a representative set of neighborhoods that had similar levels of affordable (subsidized) housing but lacked HTF units.

How We Did It

While there is no singular indicator of housing instability, most scholars agree that it encompasses a range of challenges for renters, including, but not limited to, overcrowding, frequent moves, evictions, and disproportionately high monthly housing costs.[3] For this project, the research team leveraged a composite, the Emergency Rental Assistance Prioritization Index, to measure housing instability.

This index, hereafter referred to as housing instability, was created by the Urban Institute (Washington, D.C.) to assist policymakers with identifying neighborhoods where rental assistance was most needed.[4] The measure weights ten different variables, including median monthly housing cost, percentage of renter-occupied units in multi-unit structures, percentage of cost-burdened renter households, and average renter household size, and then standardizes the percentile scores. This index, which ranges from 1 to 100, is re-coded into a categorical variable with values 1 (very low instability) to 7 (very high instability). See Appendix A for a detailed description of the measures and processes used to create this measure.

The research team employed a quasi-experimental design to examine the impact of HTF units on housing instability at the neighborhood (tract) level. To make this comparison, the research team needed to match neighborhoods that had HTF-financed housing with those that did not through the following steps:

1. Mapped the total number of affordable housing units (AHUs) at the neighborhood level (Census Tracts) as of 2013, aggregating the total number of multi-family units by funding source (HTF[5], LIHTC[6], HUD[7]).
2. Combined the neighborhood aggregates of affordable housing with prior levels of instability and various socio-demographic characteristics.

[1]Priester, M., (2025). 2024 Charlotte-Mecklenburg State of Housing Instability & Homelessness (SoHIH) Report.

[2]Colon-Bermudez, E., Emmanuel, D., Harati, R., & Renzi, K.2025). *Out of reach: The high cost of housing. National Low Income Housing Coalition.*

[3]Leopold, J., Cunningham, M., Posey, L., & Manuel, T. (2016). *Improving measures of housing insecurity: A path forward.* The Urban Institute.

[4]Batko, S., Curran-Groome, W., Axelrod, J., Chen, B., Bond, L., Spinner, B., Marconi, R., Lastowka, L., Ta, J., & Peiffer, E. (2023). *Mapping Neighborhoods with the Highest Risk of Housing Instability and Homelessness.* The Urban Institute.

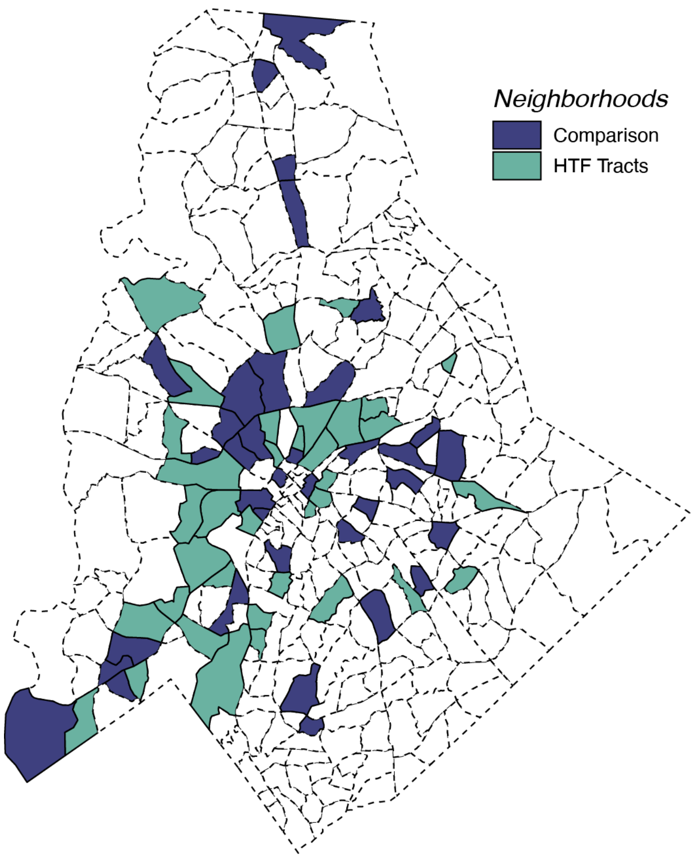
[5]The Housing Trust Fund. HTF Data Query.

[6]United States Department of Housing and Urban Development. HUD Data: Low-Income Housing Tax Credit (LIHTC): Property Level Data. https://www.huduser.gov/portal/datasets/lihtc/property.html

[7]United States Department of Housing and Urban Development. Assisted Housing: National and Local. https://www.huduser.gov/portal/datasets/assthsg.html#data_2009-2024

3. Matched neighborhoods (tracts) that had HTF multi-family properties with similar neighborhoods that had no HTF multi-family properties (see Appendix B for an overview of this process). The resultant dataset is visualized in Figure 1, demonstrating the locations of the HTF and Comparison neighborhoods.

FIGURE 1: Neighborhoods in the Resultant Matched Sample



We then employed a series of weighted regression models to investigate the determinants of neighborhood-level housing instability between 2015 and 2023. The selection of the 2015 and 2023 time points is grounded in two points:

- The operationalization of the dependent variable (housing instability) and the necessary pre-period data for robust propensity score matching require specific variables that only become consistently available starting in 2013.
- The eight-year comparison period is selected to provide a (theoretically) adequate temporal window to reflect the long-term impacts of shifting demographics, major policy changes in housing, and significant exogenous shocks (such as COVID-19).

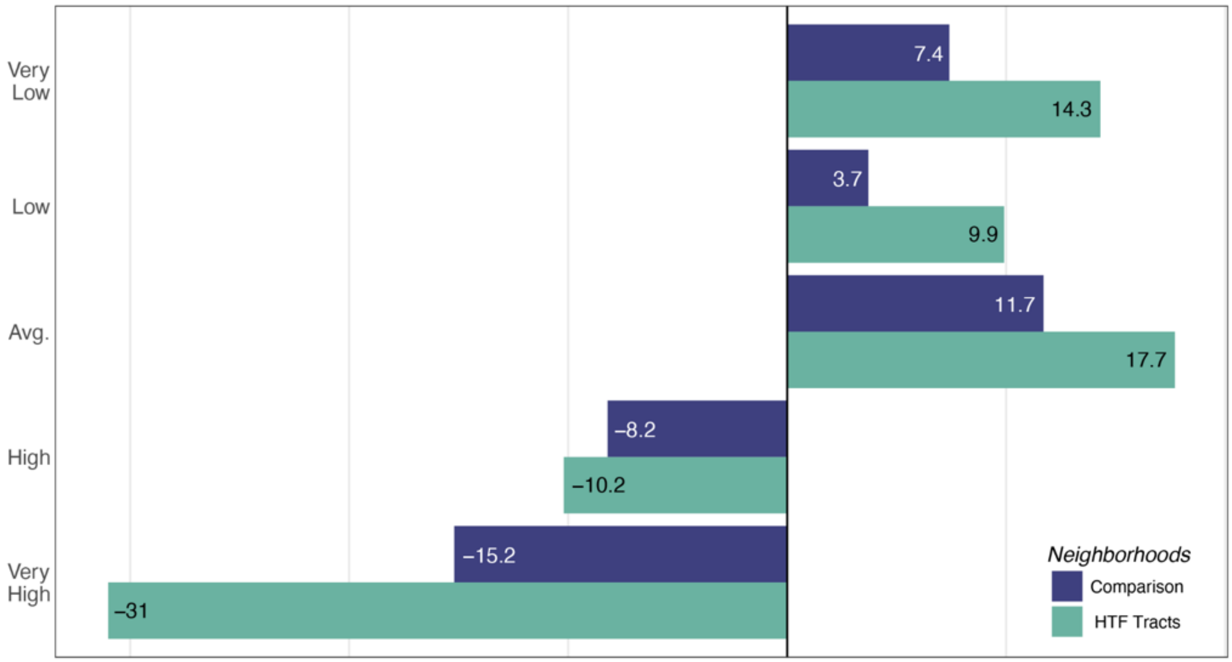
All models account for the proportion of affordable housing within and nearby neighborhoods (see Appendix C for the detailed regression results). We calculated the change in the probability (likelihood) that a neighborhood experiences varying levels of housing instability (ranging from very low to very high) between 2015 and 2023, depending on whether they have HTF units.

What We Found

In general, HTF neighborhoods were more likely to see improved housing stability over time than were the comparison neighborhoods without HTF units. HTF neighborhoods saw an increase in the likelihood of achieving lower levels of instability.

Non-HTF neighborhoods experienced a 7 percentage point increase in their likelihood of experiencing very low levels of housing instability between 2015 and 2023 (Figure 2). In comparison, HTF neighborhoods saw a greater increase, a 14 percentage point rise over the same time period.

FIGURE 2: Changes in the Predicted Probability of Instability Level by HTF-Status (2015-2023)



At the other end of the spectrum, non-HTF neighborhoods decreased from a 32% likelihood of experiencing a very high level of housing instability in 2015 to approximately 16% in 2023, representing a 15 percentage point decrease. HTF neighborhoods witnessed an even greater improvement over this time period. These areas saw a 31 percentage point reduction during the same period.

The analysis reveals that neighborhoods with HTF properties exhibit improvements in overall levels of housing instability, and these improvements are more likely to occur in these neighborhoods than in the comparison group. This suggests that incorporating HTF properties into a neighborhood may be a strategy for enhancing overall housing stability within that area.

Next Steps/Recommendations

- **Obtain more recent information on evictions:** For this study, information on evictions—an integral component of housing instability—came from the Evictions Lab, whose data only extend up to 2018. Obtaining more recent data on evictions from the Odyssey court data system would improve the accuracy of this measure.
- **Utilize a robust measure of housing instability:** The City and stakeholders could benefit from incorporating this measure, or other potential alternatives, into their current toolkit for assessing areas with the greatest need for rental housing.
- **Prioritize an iterative research approach:** While the findings demonstrate some promise in illustrating the mediating impact of HTF-funded multi-family units on levels of housing instability at the neighborhood level, there may be potential confounding factors influencing this relationship. It is therefore recommended that future research focus on a more rigorous study of causal pathways.

Appendix A - Creating a Neighborhood-Level Measure of Housing Instability

The process of creating a neighborhood-level housing instability, as outlined by the Urban Institute (Washington, D.C.), involves multiple steps.

We first collect several variables from the US Census Bureau's American Community Survey (ACS) related to demographics, housing costs, and renter status at the census tract level in Mecklenburg County. A key step here is interpolation. As tract boundaries change every ten years, we employ a population-weighted method to accurately adjust older data (pre-2020) to match modern 2020 tract boundaries. This ACS data is then merged with two external datasets: Eviction Lab data to obtain eviction filing counts, and Comprehensive Housing Affordability Strategy (CHAS) data to get information on low-income renters (percentage of cost-burdened renters).

A complete list of variables included in the creation of the index is as follows:

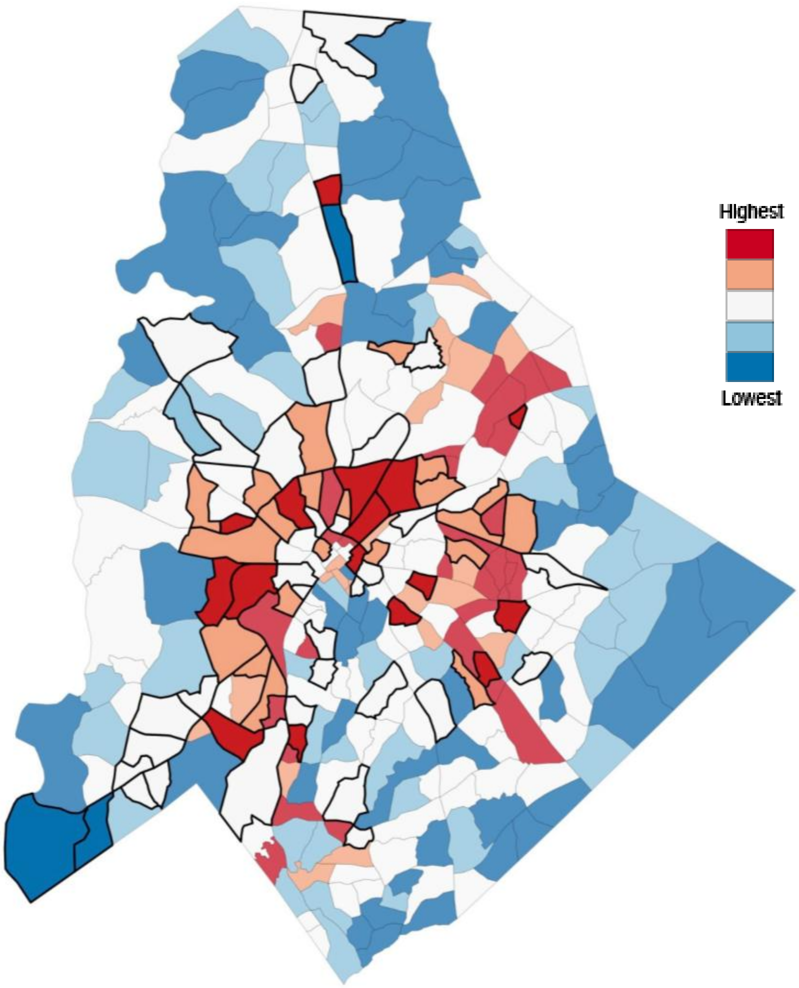
1. Median monthly housing cost
2. Renter-occupied units (%)
3. Renter-occupied units in multi-unit structures (%)
4. Cost-burdened renter households (%)
5. Extremely low–income renters (%)
6. Average renter HH size
7. Black/African American (%)
8. Asian (%)
9. Hispanic (%)
10. Other non-white (%)

Once all the data is gathered and aligned to the same geography, it is then standardized (scaled) so they can be fairly compared. The code then groups these standardized indicators into three thematic "sub-indexes": a housing sub-index (housing cost, share of renters), an income sub-index (cost-burden, low-income renters), and a household characteristics sub-index (race, household size). Finally, the code builds the housing instability index using a Weighted Quantile Sum (WQS) regression to determine how much "weight" or importance each of the three sub-indices (housing, income, and household) has in relation to the eviction filing rate.

The model generates a final set of weights, which are then applied to each tract's sub-index scores to calculate a single, comprehensive total_index. This total_index is the final neighborhood-level housing instability score, which is then converted to a percentile (1-100) for more straightforward interpretation.

Figure A1 plots the results of the index calculation. Instead of plotting the raw index values, however, the map displays the **categorical classification** of these scores**.**

Figure A1: Map of Housing Instability in Mecklenburg County, 2023



Note: While the figure includes the level of housing instability for all Census Tracts in Mecklenburg County, the research team differentiated the neighborhoods within the matched comparison set by outlining their borders and making the other neighborhoods more transparent.

Areas with the "**Highest**" hue represent tracts with weighted indexes ranging from 86 to 100, while the next highest category saw indexes ranging from 72 to 85. On the opposite end of the spectrum, tracts with the "**Lowest**" hue ranged from 1 to 15, while the second-lowest category ranged from 16 to 29. The map illustrates the spatial distribution of housing instability, confirming that the WQS index results have been successfully categorized and mapped across the county.

Appendix B - Creating the Matched Sample for Comparison

Matching neighborhoods (tracts) allows the analysis to more robustly determine the causal effect of Housing Trust Fund units on housing instability. As the placement of HTF properties is not random, what is technically referred to as "assignment to the treatment", it is imperative to select a control group (tracts without Housing Trust Fund units) that is as similar as possible to the treatment group (tracts with Housing Trust Fund units).

This is achieved through the process of "balancing" a series of covariates or potential influences on a neighborhood receiving HTF properties, such as instability, other forms of subsidized housing, the proportion of renters, the area's economic characteristics, and demographics.

- Treatment (DV): binary indicator for the presence of HTF-funded properties within a neighborhood as of 2023.
- Index: categorical grouping of the comprehensive Housing Instability Index.
- Development Assistance: binary indicator for the presence of other types of subsidized housing units, e.g., LIHTC units.
- Other covariates: log-transformed median rent and percentages of renter-occupied units, vacant units, unemployment, and non-Hispanic Black/African American.[1,2]

Table B1: Differences between Matched Sample (Treated-Comparison) and All Tracts

		All Tracts		Comparison Tracts	
	Treated	Average	Difference	Average	Difference
Instability	4.86	3.85	1.011	4.806	0.056
Subsidized	0.56	0.10	0.458	0.528	0.028
Rent (ln)	6.53	6.39	0.138	6.465	0.064
Renter	0.54	0.39	0.154	0.506	0.034
Vacant	0.12	0.09	0.029	0.107	0.009
Unemployment	0.17	0.10	0.068	0.148	0.020
Race (AA)	0.50	0.27	0.233	0.456	0.045

[1] Walker K, Herman M (2025). *tidycensus: Load US Census Boundary and Attribute Data as 'tidyverse' and 'sf'-Ready Data Frames*. R package version 1.7.3, https://walker-data.com/tidycensus/.
[2] U.S. Census Bureau, "American Community Survey 5-Year Estimates: Comparison Profiles 5-Year," 2013, <http://api.census.gov/data/2013/acs/acs5>; U.S. Census Bureau, "American Community Survey 5-Year Estimates: Data Profiles 5-Year," 2013, <http://api.census.gov/data/2013/acs/acs5>;

Appendix C - Regression Models Used for Analysis

The analysis employs a Difference-in-Differences (DiD) approach on a matched sample. The sample is restricted to matched observations by excluding records that are missing the treatment status or the propensity score. Key variables are then generated, including the binary time indicator (1 for 2023, 0 for 2015) and the primary DiD interaction term.

A critical preliminary step involves conducting a t-test on the outcome variable in the pre-treatment year (2015) to confirm that the treatment and control groups started at similar levels, thereby providing evidence to support the parallel trends assumption for the DiD design.

The core estimation strategy involves weighted logistic regression, with Inverse Probability of Treatment weights and standard errors clustered at the subclass level to account for dependence within matched sets. The most basic model isolates the Average Treatment Effect on the Treated (ATT) before expanding to include the dosage of HTF units (the percent of total units provided through the HTF). A series of increasingly robust models is estimated, progressively adding important control variables—such as demographics, socioeconomic factors, alternative development indicators, and spatially lagged program variables.

Table C1: Ordered Logistic Regression Models

	(1)	(2)	(3)	(4)	(5)	(6)
HTF	-0.235		-0.197	1.390*	1.253*	1.369*
	(0.439)		(0.520)	(0.766)	(0.761)	(0.708)
Time	0.408	-0.220	0.411	-4.776	-4.357	-2.492
	(0.257)	(0.346)	(0.259)	(5.354)	(5.890)	(6.728)
HTF x Time	-0.569		-0.973*	-2.203	-2.279	-2.354*
	(0.349)		(0.533)	(1.396)	(1.429)	(1.263)
HTF(%)		-1.401	-1.147	-6.117*	-7.368*	-7.506**
		(4.406)	(4.892)	(3.684)	(3.853)	(2.948)

Time x HTF(%)	3.182	6.039	3.930	6.284	6.856
	(5.175)	(5.835)	(7.182)	(8.069)	(7.022)
Renter Units(%)			15.465***	15.542***	15.606***
			(2.577)	(2.618)	(2.368)
Vacant Units(%)			-10.607	-13.399	-11.700
			(12.720)	(13.337)	(15.018)
Unemployment			-1.047	-1.939	-5.004
			(6.237)	(6.222)	(6.685)
Black/AA(%)			1.955	1.900	3.024
			(1.858)	(1.918)	(2.157)
Hispanic(%)			4.531	4.863	7.147
			(3.087)	(3.188)	(4.358)
Median Rent(log)			-4.353*	-4.340*	-4.848*
			(2.309)	(2.404)	(2.841)
HH_Inc(log)			-2.298*	-2.134	-1.735
			(1.309)	(1.454)	(1.652)
Subsidized(%)				6.890	6.955
				(4.294)	(4.474)

HTF Spatial Weight						-37.381**
						(17.014)
Subsidized Spatial Weight						24.971**
						(11.890)
Observations	144	144	144	144	144	144

Note: Clustered standard errors in parentheses; * p<0.1 ** p<0.05 *** p<0.01

The post-estimation analysis utilizes the margins command to provide an interpretable, policy-relevant breakdown of the results from the Ordered Logit model. Specifically, we calculate the predicted probability for two outcome levels of the categorical variable: the lowest level of instability and the highest level of housing instability. These probabilities are estimated for all four treatment-time combinations that constitute the DiD design: treated versus untreated, and pre-period versus post-period.