The Low Income Housing Tax Credit & Mental Health

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Prairie Estates | Inver Grove Heights, MN | Placed Into Service 2019 | 40 Low-Income Units

Abstract

The discrepancy between the demand for and supply of affordable housing in the United States continues to grow. The Low Income Housing Tax Credit (LIHTC), which incentivizes the private market to provide affordable housing, is one method employed to increase the quantity of affordable housing. Given its current size and impending expansion, understanding the impacts of the LIHTC is important. Established relationships between unaffordable housing and worse mental health outcomes prompt the exploration of whether increased availability of LIHTC units, which should reduce the cost-burden of rent, improves the mental health outcomes of those that live in the areas where LIHTC units are placed. The following employs a multiple variable linear regression model, to which county and year fixed effects and an interaction term are added, to explore this relationship. Results indicate that the LIHTC program improves mental health outcomes, but that this effect diminishes in counties with higher poverty rates.

Introduction & Literature

In March of 2023 the National Low Income Housing Coalition's report, *THE GAP: A Shortage of Affordable Homes*, identified that only 33 affordable housing units are available for every 100 renter households with incomes equal to or below 30% of the area median income (AMI), and only 55 affordable housing units are available for every 100 renter households with incomes between 31% and 50% of the AMI. (The National Low Income Housing Coalition 2023, 6) Further, a March 2023 article from the United States Census Bureau reported that in 2021, 20.1 million[1] renter households were cost-burdened, exceeding the *30% of income spent on housing* threshold, a roughly one million renter household increase from 2019. (United States Census Bureau, 2023) The existing and growing shortage of affordable housing in the United

[1] Estimated total number of rental households in 2019 was ~ 44 million (Pew Research Center, 2021)

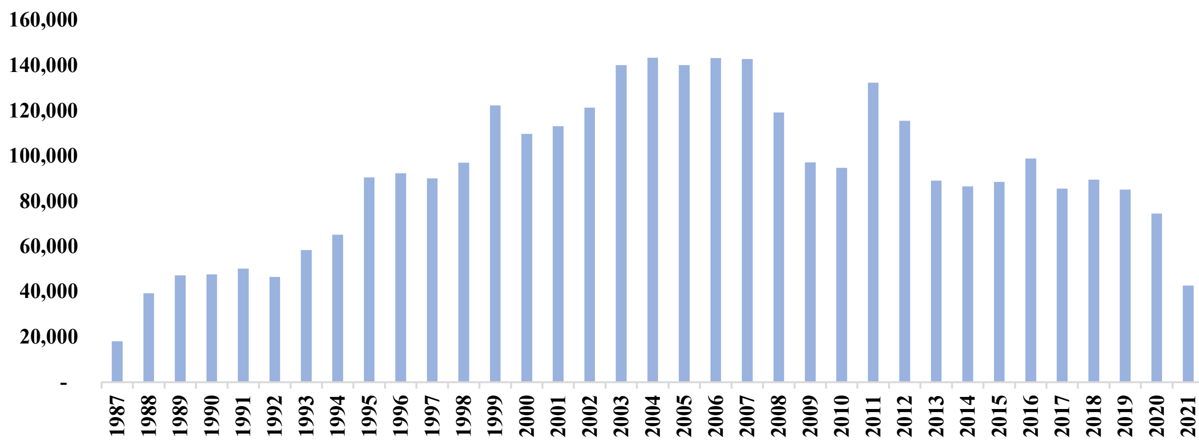
States is not without consequences: studies have identified associations between exposure to unaffordable housing and worse mental health outcomes, (Baker *et al.* 2020, Bentley *et al.* 2011) as well as associations between financial distress and worse mental health. (Ryu & Fan 2022, Butterworth *et al.* 2009) The Low Income Housing Tax Credit (LIHTC), which incentivizes the generation of affordable housing, is one available remedy for the ongoing lack of affordable housing. It operates as a subsidy employed to move the market to produce the socially optimal quantity of affordable housing.[2] In theory, reducing the cost-burden of rent via the LIHTC program, which provides additional affordable housing, will improve mental health outcomes in U.S. counties in which the LIHTC projects reside. Whether the availability, or rather the quantity, of LIHTC units indeed bears a relationship with mental health outcomes, and the direction of such relationship, is the focus of this study, providing a novel dimension of evaluation for the LIHTC program in light of continued program expansion.

Introduced in the Tax Reform Act of 1986 (Congress, 1986) and made permanent in the Omnibus Budget Reconciliation Act of 1993, (Congress, 1993) the LIHTC program offers a tax credit to those who *construct*, *acquire*, or *restore* housing to be occupied by low to moderate income tenants. (Tax Policy Center, 2022) Annually, State Housing Agencies are allotted a tax credit from the IRS, determined at a per capita rate; a minimum allotment is reserved for low-population states. (Internal Revenue Service, 2015) State Housing Agencies are responsible for assessing project submissions and allocating funds. Once approved, tax credits are received for 10 years pro rata. Projects must meet IRS compliance for fifteen years and remain under State Housing Agency authority for an additional fifteen years. It is estimated that there are currently 3.7 million LIHTC units in service nationally (NCSHA), and that over 100,000 additional units

[2] See Appendix 1 for graph with subsidy shown

are placed into service annually. (Tax Foundation, 2020)[3] Figure 1 shows the LIHTC units placed into service annually from 1987 to 2021.

FIGURE 1 : Annual LIHTC Units Placed Into Service (1987-2021)



Today, the federal government forgoes roughly $9 billion (USD) in tax revenue to support the LIHTC program, (HUD Office of Policy Development and Research) the equivalent of approximately 12.5% of the U.S. Department of Housing and Urban Development (HUD) 2023 Enacted Budget, which supports 24 housing and community programs and management and administrative expenses. (U.S. Department of Housing And Urban Development, 2023) Further, the program continues to expand: the bipartisan Affordable Housing Credit Improvement Act (AHCIA) was introduced in May of 2023, and if passed is expected to generate 1.93 million units over the next decade (Novogradac, 2022), increasing the current LIHTC unit supply of 3.7 million by roughly 52%. As of January 2024, the bill has not yet been passed. Exploring the impact of the LIHTC program on mental health outcomes is important considering the size of the current program, its impending expansion, and the rise in mental health problems during and post

[3] See Appendix 2 for additional LIHTC program details

the Covid-19 Pandemic. (KFF, 2023) Such research augments and informs the decisions of policy makers determining best ways to generate affordable housing, mitigate or diminish mental health problems, or both.

Over the past two decades, economic literature exploring the LIHTC program has primarily focused on the crowding out of unsubsidized private rental housing development, spillover price impacts, and the siting and proximity of LIHTC projects. Notable research from Nathaniel Baum-Snow and Justin Marion, using LIHTC data from 1987 to 2005, found that LIHTC projects crowd out new unsubsidized rental construction, increase owner occupied housing turnover, reduce local median income, and generate positive spillover price effects on houses in "declining and stable" (Baum-Snow & Marion 2009, 665) neighborhoods, but not in gentrifying neighborhoods, where the effect of LIHTC projects on house prices is null. Similarly, Matthew Freedman and Tamara McGavock, employing LIHTC data from 2004 to 2019, found that LIHTC projects crowd out unsubsidized, private rental housing development and are associated with decreases in income levels; Freedman & McGavock also find LIHTC projects to be associated with increases in poverty rates. The reduction in income and increase in poverty rates reflect the migration of low-income individuals to LIHTC projects. (Freedman & McGavock 2015, 832) Further, by separating spillover price impacts by area income levels, Rebecca Diamond and Tim McQuade, employing LIHTC unit data from 129 counties across 15 states between the years 1987 and 2012, find negative spillover effects on house prices in high-income, low-minority areas, positive spillover effects on house prices in high-minority areas, and positive spillover effects on house prices in low-income areas. Research on LIHTC properties placed into service from 1987 to 2014 in Cook County completed by Richard Voith *et al.*, however, determined that both individual and concentrations of LIHTC projects produce longterm positive price spillover effects on houses in surrounding neighborhoods, *regardless of a neighborhood's income composition*, and that the positive spillover effects are felt more strongly closer to LIHTC projects. As the United States is such a diverse nation, studies concerning differing regions and cities, for different time periods often come to varying conclusions; the external validity of such studies remains a concern. Consistencies across literature include the determination that LIHTC projects are more likely to be located in *worse neighborhoods*, as defined by variables such as poverty rates, labor markets, environmental quality, and school quality, (Ellen *et al.* 2017, Van Zandt & Mhatre 2009) and that LIHTC projects are likely to be developed together in clusters. (Oakley 2008, Van Zandt & Mhatre 2009, Dawkins 2013)

Recent research completed in the field of preventative health has endeavored to assess the relationship between the LIHTC program and social behavior. Meghan E. Shanahan *et al.* determined relationships at both the county and state level between accessibility of LIHTC units and a 4% to 6% reduction in "CPS (Child Protective Services) reports for overall maltreatment, physical abuse, and neglect." (Shanahan *et al.* 2022, 732) Translating these results to the population level for the year 2015, a 4% to 6% reduction equates to 72,000 to 108,000 fewer CPS reports, an arguably economically significant impact which suggests expansion of the LIHTC program as an avenue for CPS report reduction. Also exploring LIHTC projects and social behavior, Anna E. Austin *et al.* determined an association between LIHTC availability and reduced intimate partner violence (IPV) related homicide rates. (Austin *et al.* 2022, 3)

Non-LIHTC housing programs and health outcomes have also been addressed in economic literature. Whitney Denary *et al.* found reduced psychological distress amongst low-income renters receiving rental assistance, when compared to those on a waiting list for rental assistance. (Denary *et al.* 2021) Additionally, studies have found reduced psychological distress amongst public housing residents, (Fenelon *et al.* 2017) and reduced asthma related emergency room visits amongst children living in public or multifamily housing. (Boudreux *et al.* 2020) Broadly, literature has provided exploration of (1) the LIHTC program and social behavior outcomes and (2) rental assistance and health outcomes but has not specifically addressed the LIHTC program and mental health outcomes, the gap in which this paper is focused.

Data

This project employs panel data with 3,142 U.S. counties across the period 2014-2020, for a total of 21,994 observations.[4] Data for the dependent variables and select control variables was sourced from University of Wisconsin Population Health Institute's County Rankings & Roadmaps (CR&R) database, which compiles county level data and produces a ranked county report annually. The variables used from the CR&R database were initially collected from the Behavioral Risk Factor Surveillance System (BRFSS), which collects data from 400,000+ adults in the U.S. annually via telephone survey (BRFSS, 2023), the Small Area Health Insurance Estimates (SAHIE) database, and the U.S. Census Population Estimates Program (PEP). Additionally, data for the remaining control variables was sourced from the Small Area Income and Poverty Estimates (SAIPE) and the United States Bureau of Labor Statistics (USBLS).

The data for the Low-Income Housing Tax Credit projects was sourced from the United States Housing and Urban Development Department database. (HUD Office of Policy Development and Research) The project level data was aggregated by total units to the county level. To best represent the number of total units in a county each year, only units placed into service the year of interest and 29 years prior were included in the summation. The placed into

[4] See Appendix 3 for complete data dictionary (variables, descriptions, sources)

service (PIS) year was utilized rather than the year the credit was allocated to best capture when an LIHTC project's societal impact begins taking effect. The implementation of a 29-year look-back reflects the program's stipulation that projects must meet low-income conditions 30 years post PIS. Whether projects remain affordable after 30 years is not documented, and thus they are excluded after contractual expiration.[5]

Once aggregated to county level, the data were normalized to the county population in the appropriate year via a crude rate, or a rate that measures a variable per a set population :

$$lihtc_{c,y} = (lihtc\_raw_{c,y} / population_{c,y}) * 1000$$

The crude rate is interpreted as the *number of lihtc units per 1,000 population in a county in a given year*. Finally, the *lihtc* variable was lagged one year to reflect that potential impacts from LIHTC projects are not immediate. Additionally, as noted by Shanahan *et al.*, without a 1-year lag, it is possible that the dependent variable could include observations measured before the LIHTC project was placed into service. (Shanahan et al. 2022, 729) For a 1-year lag, the lihtc data from 2013-2019 is combined with 2014-2020 data for all other variables. LIHTC projects with missing county codes, with no certain placed in service date or no placed in service confirmation, that are located in U.S. territories, or with missing total number of units were not included in the total unit count for each county, in each year. Further, projects identified as no longer monitored for unidentified reasons by the IRS or State Agencies were not included.

Table 1 features descriptive statistics. On average, counties have 757 LIHTC units, and 5.09 LIHTC units per 1,000 population. The maximum LIHTC units in a county in a given year is 74,364, and the maximum LIHTC units per 1,000 population in a county in a given year is

[5] Appendix 4 indicates the years from which units were summed for each year included in the data set.

69.74. On average, 13.56% of a county's population experience poor mental health more than 14 of the past 30 days. The maximum percent of a county's population experiencing poor mental health more than 14 of the past 30 days is 26.3%.

TABLE 1 : Descriptive Statistics[6]

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
st_cty_fips	28,278	30,379	15,166	1,001	56,045
year	28,278	2,016	2.582	2,012	2,020
lihtc_raw	25,136	757.0	3,092	0	74,364
lihtc_LI_raw	25,136	660.5	2,675	0	69,393
pop_est	25,136	132,664	470,769	86	1.011e+07
lihtc_u	25,136	5.090	5.113	0	69.74
lihtc_LI_u	25,136	4.531	4.656	0	69.08
poverty	21,994	15.39	6.202	2.600	56.70
med_hh_inc	21,994	51,768	13,883	21,658	160,305
unemployment	21,994	5.202	2.146	0.800	24.60
smoking	21,994	19.05	4.115	0	44.57
drinking	21,994	17.91	3.444	0	31.01
mental	21,994	13.56	2.824	0	26.30
uninsured	21,994	12.06	5.203	2.068	41.44
white	21,994	76.29	20.11	2.686	98.61
female	21,994	49.90	2.267	26.51	57.01
age	21,994	18.85	4.722	4.140	59.06
lihtc	25,136	5.090	5.113	0	69.74
lihtc_LI	25,136	4.531	4.656	0	69.08
lihtc_2	21,994	5.014	5.039	0	67.11
lihtc_LI_2	21,994	4.462	4.585	0	67.11
county	28,278	1,572	907.0	1	3,142
lihtc_pov	21,994	85.72	114.0	0	2,266
yr14	28,278	0.111	0.314	0	1
yr15	28,278	0.111	0.314	0	1
yr16	28,278	0.111	0.314	0	1
yr17	28,278	0.111	0.314	0	1
yr18	28,278	0.111	0.314	0	1
yr19	28,278	0.111	0.314	0	1

[6] Descriptive Statistics for dataset with 2020 observation dropped available upon request

Various challenges were revealed in sourcing data for this project. The LIHTC program is particularly difficult to evaluate because individual data on tenants is not publicly available due to privacy and confidentiality concerns. Subsequently, it is not possible to track the specific mental health outcomes of tenants pre and post moving into an affordable housing unit in an LIHTC project. Given this limitation, the project employs county level measures. As select counties across the U.S. encompass both vast wealth and poverty, it is possible some effects are averaged out or masked. Additionally, county level data concerning mental health, such as hospitalizations due to mental health, proved difficult to access due to privacy laws. Generally, sourcing multi-year, consecutive county data presented challenges.

Data on the percent of a county that self-reports being current smokers and data on the percent of a county that self-reports excessive or binge drinking are also included in the dataset. Ultimately, *smoking* and *drinking* were not employed as the primary dependent variable in this project as substance use is determined by many factors including income, familial and childhood experiences, genetic predisposition, and more, in addition to housing insecurity and stress. (SAMHSA) As many of these factors are difficult to measure, controlling for them poses challenges. These behaviors also can result in financial strain, and thus introduce two way causality into the model.[7] Essentially, the financial strain from housing may lead to substance use; heightened substance use may lead to increased financial strain. A 2-year lag *lihtc* variable was also created to explore how the impact of the quantity of LIHTC units on mental health varies 1 year vs. 2 years after LIHTC projects are placed into service.[8] Additionally, the LIHTC project data includes a measure for the number of low-income dedicated units in each project,

[7] See Appendix 5 for regression results with *smoking* as the dependent variable and Appendix 6 for *drinking* as the dependent variable
[8] Regression results using the 2-year lag lihtc variable available upon request

however, as missing data for this measurement was more prevalent, the total unit count was employed.[9]

Empirical Model

To explore the impact of the LIHTC program on county mental health outcomes, this study employs an initial multiple variable linear regression model with controls, further modified with county fixed effects (δ_c) and year fixed effects (λ_y), and an interaction term. The dependent variable is the percent of a county experiencing poor mental health 14 or more days out of the past 30 days in a given year, the independent variable of interest is the number of LIHTC units per 1,000 population in a given county in a given year. To minimize omitted variable bias, additional control variables (B_2-B_8) which theory would predict explain the dependent variable, *mental*, and are correlated with the independent variable, *lihtc*, are included. These variables include *uninsured*, *unemployed*, *poverty*, *med_hh_inc*, *white*, *female*, and *age*. Additionally, all regressions are run with robust standard errors to correct for the heteroscedasticity of the regression models. To begin, the first regression equation includes only control variables:

$$[1]\ mental_{c,y} = B_0 + B_1 lihtc_{c,y-1} + B_2 uninsured_{c,y} + B_3 unemployed_{c,y} + B_4 poverty_{c,y} + B_5 med\_hh\_inc_{c,y} + B_6 white_{c,y} + B_7 female_{c,y} + B_8 age_{c,y} + e_{c,y}$$

Next, county and year fixed effects are added. The included county fixed effects control for all differences that vary across counties but that are constant over time such as geography. The included year fixed effects control for all differences that vary over time but not across counties such as inflation rates. Both county and year effects are included in the second regression equation:

[9] Regression results using low-income lihtc variable available upon request

$$[2]\ mental_{c,y} = B_0 + B_1 lihtc_{c,y-1} + B_2 uninsured_{c,y} + B_3 unemployed_{c,y} + B_4 poverty_{c,y} + B_5 med\_hh\_inc_{c,y} + B_6 white_{c,y} + B_7 female_{c,y} + B_8 age_{c,y} + \delta_c + \lambda_y + e_{c,y}$$

To allow the effect of the number of LIHTC units per 1,000 population on mental health outcomes to vary by the percent of a county in poverty, an interaction term between the variables $lihtc_{c,y-1}$ and $poverty_{c,y}$ is included in the third regression equation:

$$[3]\ mental_{c,y} = B_0 + B_1 lihtc_{c,y-1} + B_2 uninsured_{c,y} + B_3 unemployed_{c,y} + B_4 poverty_{c,y} + B_5 med\_hh\_inc_{c,y} + B_6 white_{c,y} + B_7 female_{c,y} + B_8 age_{c,y} + B_9 (lihtc_{c,y-1}\_\ poverty_{c,y}) + \delta_c + \lambda_y + e_{c,y}$$

Finally, as the Covid-19 pandemic commenced in March of 2020 and arguably had considerable impact on variables included in this study, the three models above were re-run with observations from the year 2020 dropped. While the Covid-19 pandemic was experienced throughout the United States, it began a quarter of the way into the year, spread to different regions at different times, and generally impacted regions differently. It is possible that measurements for the dependent variable, *mental*, were completed before the pandemic began, were completed in regions where spread had not yet occurred or were completed in regions where spread had occurred greatly, for instance. It is possible that these differences are accounted for within the county fixed effects, however, because the year 2020 was so abnormal, models 4 - 6 are run with 2020 observations dropped.

Results

Table 2 includes the results for all regression models. All coefficients are tested for statistical significance using a two-tailed t-test where the null hypothesis is the coefficient of interest, B_1, is equal to zero and the alternative hypothesis is the coefficient of interest is not equal to zero. Calculated t-stats are considered at the 90% confidence level (t-stat > |1.645|), the 95% confidence level (t-stat > |1.96|), and the 99% confidence level (t-stat > |2.58|).

In the first model, shown in the first column of Table 2, the coefficient of interest is B_1, the coefficient on the *lihtc* variable. B_1 is statistically significant at 1% level, and indicates that on average, holding the included control variables constant, a one LIHTC unit increase per 1,000 population in a county is correlated with a 3.83% increase in the percent of individuals who self-report poor mental health more than 14 out of the past 30 days. Without county or year fixed effects, the model predicts an increase in LIHTC units to be correlated with worse mental health outcomes. These results fit with previous findings that LIHTC projects are more likely to be located in *worse areas*. The adjusted R^2 for Model 1 is 0.293, indicating that 29.3% of the variation in the dependent variable, *mental*, is explained by the included independent variable, *lihtc*, and the control variables.

In the second model which is shown in the second column of Table 2, the coefficient of interest is B_1, the coefficient on the *lihtc* variable. B_1 is statistically significant at 1% level, and indicates that on average, holding the included control variables constant, a one LIHTC unit increase per 1,000 population in a county is correlated with a 3.55% decrease in the percent of individuals who self-report poor mental health more than 14 out of the past 30 days. The adjusted R^2 for Model 2 is 0.883, indicating that 88.3% of the variation in the dependent variable, *mental*, is explained by the included independent variable, *lihtc*, and the control variables. Many factors impact mental health, such as genetics and family life, that are difficult to quantify or do not have available data at the county level, so 88.3% of the variation in *mental* explained is satisfactory. Arguably, this result is economically significant: for example, if a new LIHTC project with 30 units were to be introduced into a county with a population of 100,000, the crude rate would increase by 0.3. Subsequently, the percent of the county experiencing poor mental health more than 14 out of the past 30 days would decrease by (3.55*0.3) 1.065%. This translates to 1,065 fewer people experiencing poor mental health. In this same county, a new LIHTC project with 200 units, on average, would translate to 7,100 fewer people experiencing poor mental health more than 14 out of the past 30 days. Additionally in Model 2, the coefficients on *poverty*, *med_hh_inc*, *uninsured*, *female*, and *age* are significant at the 1% level and have the expected directional effect. For example, the coefficient on *poverty* is positive, indicating that counties with a larger portion of the population experiencing poverty have an increased percent of the population experiencing poor mental health.

In the third model, shown in the third column of Table 2, the coefficient of interest is B_9, the coefficient on the interaction term between the variables $lihct_{c,y}$ and $poverty_{c,y}$. B_9 is significant at the 1% confidence level, and indicates that on average, holding the included control variables constant, a 1% increase in the percent of a county experiencing poverty, correlates with a .343% decrease in the impact of $lihtc_{c,y}$ on $mental_{c,y}$. As the coefficient on $lihtc_{c,y}$ is negative, the positive coefficient on the interaction term implies that the impact of $lihtc_{c,y}$ on $mental_{c,y}$ is smaller in counties with higher poverty rates. While the coefficient may at first appear small, it is arguably economically significant: for example, on average, a 10% increase in a county's poverty rate translates to a (10*.34) 3.4% decrease in the impact of the *lihtc* on *mental*. For counties with poverty rates above 26.47%, the impact of *lihtc* on *mental* inverses: an increase in *lihtc* correlates with worse mental health outcomes.

In models 4 – 6, shown in the fourth, fifth, and sixth columns of Table 2, all coefficients of interest are larger (more positive or more negative) than in models 1 – 3, indicating that the impact of the LIHTC program on mental health outcomes was greater before the Covid-19 pandemic. The adjusted R^2 is also slightly larger in models 4 – 6 when compared to models 1 – 3. These results suggest further exploration of the LIHTC program and mental health outcomes should be done when additional post-2020 data is available.

The internal validity, or whether the "statistical inferences" (Stock & Watson, 288) of this study can appropriately be applied to the population of interest in this study, the United States, should be considered. As detailed in Stock & Watson's *Introduction to Econometrics 4th Edition*, internal validity considers omitted variable bias, functional form, measurement error and errors-in-variables bias, missing data and sample selection bias, simultaneous causality, and sources of inconsistency of OLS standard errors. (Stock & Watson, 291-301) For omitted variable bias to be present, a variable in the error term must be correlated with the independent variable of interest and explain the dependent variable. It is possible that OVB exists within this study: a variable such as environmental quality, which could explain the dependent variable *mental* and be correlated with the independent variable *lihtc*, could introduce OVB. Regarding functional form, as many of the included variables are measured as percentages, including the square or natural log of variables does not provide meaningful or interpretable results. Measurement error and errors-in-variables bias arguably pose the greatest threat to the internal validity of this study. As this study employs BRFSS data, which is collected via telephone, select portions of the population, notably, those without phones, could be excluded from the data, posing sample selection bias. Further, as the BRFSS is collecting data concerning health, it is plausible that people are not completely truthful or forthcoming with their mental health experiences. It is also possible that individuals may be giving best guess answers about how often they are experiencing poor mental health, rather than exact answers. Regarding missing data, various projects have missing county code data, total unit data, and PIS data; these projects are *not* included in the count of total LIHTC units in a county in a given year. Projects with missing data for the variables of interest listed above were distributed across all 50 states; it is assumed that data is missing in a random manner, not systematically. If, however, data is actually systematically missing, this could introduce bias. Finally, it is not likely simultaneous causality is introduced in this study; the prevalence of poor mental health outcomes likely does not explain the change in the number of LIHTC units per 1,000 population.

External validity, or the assessment of whether the statistical inference of a study can be applied or transferred to other populations, (Stock & Watson, 290) should also be considered. As this study includes counties across the United States in the dataset, it is not plausible that the results can be properly or easily transferred to other countries. The United States has a unique government and market structure. Significant consideration would need to be given to a country's unique social, market, and political systems when trying to transfer results.

TABLE 2 : Regression Results

				2020 Observations Dropped		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
lihtc	0.0383***	-0.0355***	-0.0908***	0.0261***	-0.0374***	-0.0988***
	(0.00354)	(0.00901)	(0.0159)	(0.00365)	(0.00973)	(0.0178)
lihtc_pov			0.00343***			0.00359***
			(0.000901)			(0.000937)
poverty	0.273***	0.0416***	0.0211**	0.315***	0.00917	-0.0112
	(0.00616)	(0.00624)	(0.00867)	(0.00664)	(0.00603)	(0.00852)
med_hh_inc	4.05e-05***	-3.44e-05***	-3.36e-05***	2.06e-05***	-6.09e-05***	-6.01e-05***
	(2.33e-06)	(2.89e-06)	(2.88e-06)	(2.41e-06)	(3.40e-06)	(3.41e-06)
unemployment	0.0596***	-0.0179*	-0.0143	-0.261***	-0.0699***	-0.0684***
	(0.00949)	(0.00922)	(0.00925)	(0.0119)	(0.0138)	(0.0139)
uninsured	0.0136***	0.0506***	0.0502***	-0.0218***	0.0277***	0.0278***
	(0.00419)	(0.0124)	(0.0124)	(0.00409)	(0.00704)	(0.00705)
white	0.0112***	-0.0344	-0.0375*	0.00521***	-0.0395	-0.0427*
	(0.00125)	(0.0226)	(0.0227)	(0.00128)	(0.0254)	(0.0256)
female	0.132***	0.0920***	0.0915***	0.151***	0.0894***	0.0890***
	(0.00759)	(0.0349)	(0.0338)	(0.00823)	(0.0303)	(0.0297)
age	0.107***	-0.0970***	-0.0962***	0.0822***	-0.0777***	-0.0766***
	(0.00390)	(0.0220)	(0.0221)	(0.00407)	(0.0176)	(0.0177)
yr14		-5.366***	-5.346***		-5.348***	-5.339***
		(0.0714)	(0.0705)		(0.0724)	(0.0716)
yr15		-4.709***	-4.692***		-4.770***	-4.765***
		(0.0646)	(0.0644)		(0.0547)	(0.0543)
yr16		-4.037***	-4.022***		-4.131***	-4.126***
		(0.0609)	(0.0608)		(0.0471)	(0.0468)
yr17		-3.166***	-3.151***		-3.270***	-3.266***
		(0.0461)	(0.0462)		(0.0332)	(0.0330)
yr18		-0.950***	-0.936***		-1.050***	-1.047***
		(0.0385)	(0.0387)		(0.0191)	(0.0190)
yr19		0.0532	0.0643**			
		(0.0329)	(0.0327)			
Constant	-2.860***	16.82***	17.31***	-0.826	19.45***	19.97***
	(0.499)	(1.886)	(1.796)	(0.527)	(1.671)	(1.612)
Observations	21,994	21,994	21,994	18,852	18,852	18,852
R-squared	0.239	0.883	0.883	0.300	0.890	0.891
Number of county		3,142	3,142		3,142	3,142

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

OLS Assumptions

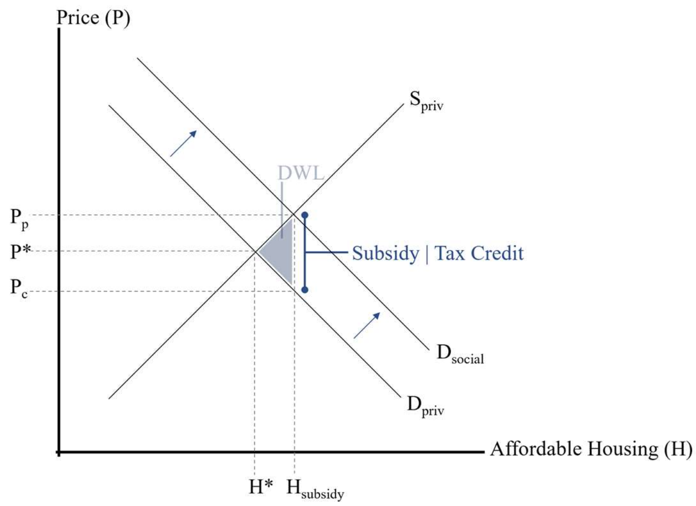
Further examining the qualities and strength of this study, the assumptions of Gauss-Markov's Ordinary Least Squares BLUE (Best Linear Unbiased Estimate) theorem can be considered. The first assumption, $E(u \mid X) = 0$, (Stock & Watson, 191) likely does not hold; there are variables in the error term, such as environmental quality, that explain the dependent variable, *mental*, and that are correlated with the independent variable, *lihtc*, so omitted variable bias is introduced into the regression. It is possible that variables in the error term are correlated with included controls, however this does not introduce bias into the model. One hindrance to this project was sourcing county level data; there are variables that would ideally be included in the regression, such as education and marriage, where data is not available at all, or is not available for multiple, consecutive years. The second assumption, Identically Independently Distributed (i.i.d.) (Stock & Watson, 183 & 332), holds: for panel data, assumption two allows a county to be related to itself over time, however, counties must be independently distributed from one another. Counties generally have enough physical spread to be considered independent. The third assumption, all variables have a finite fourth moment, (Stock & Watson, 332) holds as large outliers are unlikely; reviewing Table 1, the summary statistics tables, confirms this. For each variable, the minimum and maximum do not reveal any unexpectedly low or high figures. Additionally, this study assumes no typos in the data (ex. entering 10 units v. 100 units) The fourth assumption, no perfect multicollinearity, (Stock & Watson, 332) holds as no included variable perfectly explains another. Finally, the fifth assumption, homoscedastic errors, does not hold: it is likely that the size of the errors, conditioning on at least one of the independent variables, is not constant. To account for this, robust standard errors are employed.

Conclusion

This study aims to explore the relationship between the LIHTC program and mental health outcomes. When including control variables and county and year fixed effects, results indicate that a one LIHTC unit increase per 1,000 population in a county is correlated with a 3.55% decrease in the percent of individuals who self-report poor mental health more than 14 out of the past 30 days. In allowing for the impact of the *lihtc* variable on *mental* to vary by *poverty*, it is revealed that an increase in poverty decreases the effect of *lihtc* on *mental*; a 1% increase in the percent of a county experiencing poverty, correlates with a .343% decrease in the impact of $lihtc_{c,y}$ on $mental_{c,y}$. The relationship eventually meets an inflection point at 26.47% and inverses. The primary shortcoming of this project is the inability to make causal inferences. Mental health data on tenants pre and post moving into LIHTC housing remains confidential or is not collected at all, resulting in the inability to track individuals and households over time. Overall, results from this study suggest further exploration of the LIHTC program and mental health outcomes, potentially employing data from the Covid-19 pandemic, when rents increased considerably, (The Washington Post, 2023) to observe varying impacts. It is possible that the LIHTC program is one way to mitigate poor mental health outcomes, however further research and exploration is necessary.

Appendix

(1) Employing A Tax Credit to Achieve Social Optimal Affordable Housing Production



(2) Additional LIHTC Information

The program has two tax credit avenues typically referred to as the "four percent credit" and the "nine percent credit." Projects placed into service in 1987 were eligible for: a fixed 9% credit if new and not federally subsidized for the taxable year, a fixed 4% credit if new and federally subsidized for the taxable year or converted housing. Projects placed into service between 1988 and July 31, 2008, were eligible as stated: "the applicable percentage was prescribed by the IRS such that it would yield, over the 10-year credit period, an amount of credit having a present value equal to: [1] 70% of the qualified basis of a new building that is not federally subsidized for the taxable year, and [2] 30% of the qualified basis of (1) a new building that is federally subsidized for the taxable year or (2) an existing building." (Internal Revenue Service, 2015) Projects placed into service after July 30, 2008, are eligible as stated: "the applicable percentage is determined by the IRS such that the credit over the 10-year credit period will yield a present value equal to: [1] 70% of the qualified basis of a new building that is not federally subsidized for the taxable year, and [2] 30% of the qualified basis of all other buildings." (Internal Revenue Service, 2015)

(3) Data Dictionary

Variable	Definition	Source
st_cty_fips	county codes	-
year	year	-
lihtc_raw	Total lihtc units by county, by year	HUD
lihtc_LI_raw	Total low-income lihtc units by county, by year	HUD
pop_est	county population in a given year	United States Census Bureau
lihtc_u	*lihtc_raw* normalized to county population with a crude rate	HUD
lihtc_LI_u	*lihtc_LI_raw* normalized to county population with a crude rate	HUD
poverty	% of the population in a county living in poverty in a given year	Small Area Income and Poverty Estimates
med_hh_inc	median household income in a county in a given year	Small Area Income and Poverty Estimates
unemployment	% of the population in a county that is unemployed in a given year	United States Bureau of Labor Statistics
smoking	% of the population in a county in a given year that are self-report being current smokers	County Rankings & Roadmaps | BRFSS
drinking	% of the population in a county in a given year that self-report binge or excessive drinking	County Rankings & Roadmaps | BRFSS
mental	% of the population in a county in a given year that self-report experiencing poor mental health more than 14 days of the past 30 days	County Rankings & Roadmaps | BRFSS
uninsured	% of the population under 65 without health insurance in a county in a given year	County Rankings & Roadmaps | Small Area Health Insurance Estimates
white	% of the population that self-identifies as non-Hispanic white in a county in a given year	County Rankings & Roadmaps | U.S. Census Population Estimates
female	% of the population that is female in a county in a given year	County Rankings & Roadmaps | U.S. Census Population Estimates
age	% of the population that is 65 or older in a county in a given year	County Rankings & Roadmaps | U.S. Census Population Estimates
lihtc	lihtc units per 1,000 population by county, by year with a 1-year lag	HUD
lihtc_LI	lihtc low-income units per 1,000 population by county, by year with a 1-year lag	HUD
lihtc_2	lihtc units per 1,000 population by county, by year with a 2-year lag	HUD
lihtc_LI_2	lihtc low-income units per 1,000 population by county, by year with a 2-year lag	HUD
lihtc_pov	interaction term between *lihtc* and *poverty* variables	-
population	county population in a given year	United States Census Bureau

(4) LIHTC Data Inclusion Schedule

2012	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012				
2013	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013			
2014	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014		
2015	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	
2016	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
2017	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
2018	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
2019	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019

(5) Regression Results - Dependent Variable : Smoking

				2020 Observations Dropped		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
lihtc	0.00952*	-0.120***	-0.238***	0.00252	-0.131***	-0.242***
	(0.00525)	(0.0161)	(0.0271)	(0.00586)	(0.0170)	(0.0304)
lihtc_pov			0.00731***			0.00649***
			(0.00146)			(0.00156)
poverty	0.386***	0.0330***	-0.0107	0.417***	0.0303***	-0.00659
	(0.00914)	(0.0103)	(0.0147)	(0.0100)	(0.0107)	(0.0151)
med_hh_inc	-3.12e-05***	-6.78e-05***	-6.62e-05***	-3.95e-05***	-7.16e-05***	-7.01e-05***
	(3.05e-06)	(5.39e-06)	(5.43e-06)	(3.34e-06)	(5.73e-06)	(5.80e-06)
unemployment	0.0967***	-0.245***	-0.238***	-0.138***	-0.290***	-0.288***
	(0.0160)	(0.0166)	(0.0168)	(0.0216)	(0.0235)	(0.0237)
uninsured	0.00928	0.102***	0.102***	-0.0232***	0.0920***	0.0921***
	(0.00569)	(0.0175)	(0.0176)	(0.00602)	(0.0131)	(0.0131)
white	0.0567***	-0.143***	-0.149***	0.0523***	-0.169***	-0.175***
	(0.00188)	(0.0521)	(0.0521)	(0.00202)	(0.0490)	(0.0491)
female	0.0419***	0.0376	0.0366	0.0657***	0.0477	0.0469
	(0.0111)	(0.0754)	(0.0727)	(0.0124)	(0.0686)	(0.0668)
age	-0.0650***	-0.118***	-0.116***	-0.0950***	-0.0887***	-0.0867***
	(0.00582)	(0.0341)	(0.0344)	(0.00646)	(0.0308)	(0.0309)
yr14		-3.038***	-2.995***		-2.309***	-2.293***
		(0.132)	(0.130)		(0.129)	(0.128)
yr15		-3.331***	-3.296***		-2.672***	-2.662***
		(0.110)	(0.109)		(0.0955)	(0.0949)
yr16		-3.214***	-3.181***		-2.590***	-2.581***
		(0.0983)	(0.0978)		(0.0803)	(0.0799)
yr17		-3.655***	-3.623***		-3.070***	-3.062***
		(0.0781)	(0.0779)		(0.0566)	(0.0564)
yr18		0.234***	0.264***		0.784***	0.790***
		(0.0619)	(0.0623)		(0.0313)	(0.0313)
yr19		-0.539***	-0.516***			
		(0.0513)	(0.0514)			
Constant	8.868***	35.89***	36.93***	9.803***	36.87***	37.80***
	(0.721)	(4.405)	(4.207)	(0.782)	(3.918)	(3.776)
Observations	21,994	21,994	21,994	18,852	18,852	18,852
R-squared	0.395	0.590	0.592	0.406	0.622	0.623
Number of county		3,142	3,142		3,142	3,142

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(6) Regression Results - Dependent Variable : Drinking

				2020 Observations Dropped		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
lihtc	0.0132***	-0.0735***	-0.167***	0.0129***	-0.0561***	-0.135***
	(0.00386)	(0.0152)	(0.0249)	(0.00426)	(0.0158)	(0.0269)
lihtc_pov			0.00578***			0.00462***
			(0.00110)			(0.00111)
poverty	-0.183***	0.00403	-0.0305***	-0.163***	-0.00995	-0.0362***
	(0.00735)	(0.00812)	(0.0109)	(0.00774)	(0.00804)	(0.0105)
med_hh_inc	4.36e-05***	-2.16e-05***	-2.03e-05***	4.24e-05***	-1.71e-05***	-1.60e-05***
	(3.22e-06)	(4.57e-06)	(4.51e-06)	(3.55e-06)	(5.16e-06)	(5.11e-06)
unemployment	-0.142***	-0.0851***	-0.0792***	-0.236***	0.0368**	0.0386**
	(0.0110)	(0.0125)	(0.0124)	(0.0148)	(0.0180)	(0.0179)
uninsured	-0.125***	-0.0224	-0.0230	-0.134***	0.00196	0.00205
	(0.00434)	(0.0156)	(0.0156)	(0.00466)	(0.0124)	(0.0124)
white	-0.00748***	0.0754***	0.0701***	-0.00848***	0.0614***	0.0573**
	(0.00132)	(0.0253)	(0.0246)	(0.00141)	(0.0234)	(0.0229)
female	-0.327***	-0.268***	-0.269***	-0.324***	-0.241***	-0.241***
	(0.00846)	(0.0418)	(0.0418)	(0.00913)	(0.0423)	(0.0428)
age	0.0696***	0.0507	0.0521	0.0410***	0.0647**	0.0661**
	(0.00510)	(0.0319)	(0.0319)	(0.00561)	(0.0315)	(0.0314)
yr14		-2.779***	-2.745***		-2.679***	-2.668***
		(0.113)	(0.112)		(0.106)	(0.105)
yr15		-2.820***	-2.792***		-2.603***	-2.596***
		(0.101)	(0.101)		(0.0869)	(0.0868)
yr16		-2.032***	-2.006***		-1.779***	-1.772***
		(0.0913)	(0.0912)		(0.0751)	(0.0751)
yr17		-1.930***	-1.905***		-1.634***	-1.629***
		(0.0736)	(0.0734)		(0.0563)	(0.0563)
yr18		-0.340***	-0.316***		-0.0102	-0.00619
		(0.0593)	(0.0590)		(0.0350)	(0.0350)
yr19		-0.302***	-0.284***			
		(0.0490)	(0.0486)			
Constant	36.24***	28.18***	29.01***	36.90***	26.38***	27.04***
	(0.587)	(2.328)	(2.307)	(0.630)	(2.378)	(2.397)
Observations	21,994	21,994	21,994	18,852	18,852	18,852
R-squared	0.389	0.473	0.474	0.400	0.486	0.487
Number of county		3,142	3,142		3,142	3,142

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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