Ground-truthing Energy Burden in Memphis and Shelby County, TN:

Analyzing the energy impacts and health outcomes from a local government's homeowner rehabilitation program

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Introduction and Background

This study will use publicly available datasets along with qualitative assessments of interview data to explore the associations between poor housing conditions, energy burden, and incidences of poor mental health in Memphis and Shelby County, TN. Through trends analysis and regression models to investigate the relationships between these variables and qualitative dialogue with residents, this proposed research begins to find locally relevant narratives around health disparities and subsequently make recommendations to address the environmental injustices of historic practices and policies that have created such health disparities. Providing quality affordable housing is reported as one solution to address these types of health inequalities (Ige et al., 2019), suggesting that prioritizing a more stabilized housing stock could have multi-faceted benefits for municipalities (Stacy et al., 2019). Further, tracking patterns of energy insecurity can help target public sector interventions, and help prioritize assistance (Moore & Webb, 2022). This mixed methods study also seeks to identify potential policy changes for local governments to integrate health outcomes data more effectively in programmatic and policy interventions to better support healthier, resilient communities.

The burden of poor living conditions falls disproportionately on those populations that experience vulnerabilities such as limited income or lacking access to well-maintained housing conditions, and put simply those most in need are the least likely to have good quality housing (Telfar Barnard et al., 2020). Families experiencing housing instability or have history of eviction are less likely to access and utilize healthcare services, which results in poorer health outcomes for those not stably housed in safe, quality housing (Hatch & Yun, 2021). The indoor environment, especially in homes where the majority of one's time is spent, is integral to health and wellbeing (Ige et al., 2019; Palacios et al., 2021), and as such is an important consideration in health disparities research. Energy burden is a measurement of energy poverty that captures the proportion of household income spent on utility costs and follows a pattern of concentrated disadvantage similar to poor housing quality (Chen et al., 2022). Energy burden is defined for the purposes of this study as energy consumption in a residence and its associated costs in the forms of electricity and gas usage for utilities (Maxim & Grubert, 2022). High energy burden can subsequently influence what a household chooses (or foregoes) in expenditures and can force residents to keep their homes at unsafe or uncomfortable temperatures, also termed a 'heat or eat' problem (Moore & Webb, 2022). It is therefore hypothesized that positive correlations between (a) poor housing conditions and incidences of poor mental health and (b) high energy burden and incidences of poor mental health will emerge from this analysis and demonstrate that poor housing and high energy burden are factors involved in incidences of poor mental health. Poor housing conditions are defined for the purposes of this study as any type of related housing disadvantage measure (see Table 2 in later Methodology descriptions) such as physical conditions (leaks, poor temperature regulation, crowding) or compromising housing-related circumstances (multiple moves, delinquent payments, experience with eviction, energy burden). Poor mental health conditions are defined for the purposes of this study as any related mental health indicator (see Table 2 in later section) such as mental strain, financial stress, allostatic load, or similar conditions. It is expected that these types of housing-related stressors play a role in determining health outcomes.

In examining associations between variables and reporting regression coefficients, patterns can emerge that help identify how limited access to quality living environments aligns with poor health outcomes. Limitations to this approach include an inability to assign causal links between these factors, however, at least initially. In order to bring a more comprehensive and humanized voice to this analysis, a qualitative assessment of interview data can help reveal individual perceptions and lived experience regarding potential causes of compromised health, emotional challenges, financial strain, and other proxies for mental health outcomes. The aim of this research centers on exploring associations between poor housing conditions, high energy burden, and mental health first through quantitative assessment of publicly available datasets and then augment this initial exploration with qualitative information collected from resident interviews to identify individual perceptions on causes of emotional distress and poor mental health outcomes. Quantitative analysis of energy burden relief for clients receiving structural interventions will take place to determine how local public sector programs can impact energy consumption and subsequent utility costs. Additional quantitative analysis will include both non-spatial and spatial models that will account for other potentially influential socioeconomic factors that are relevant to this analysis.

Literature Review

Infrastructural policies and practices such as redlining, exclusionary zoning, and differential access to resources are widely acknowledged to have contributed to systematic health and wealth disparities (Maxim & Grubert, 2022). Policies and land use control measures protected and supported certain groups (white property owners, for example), while systematically oppressing people of color and the poor (Trounstine, 2018). Environmental justice approaches help bring greater clarity to the disparate impacts of these collective social systems and also offer opportunity to find methods to work towards more equitable outcomes in urban growth. Inequitable exposure to hazards, pollutants, and nuisances has driven interest and analysis of how environmental justice approaches can help first examine the distribution of such injustices, and also address the interventions that can help mitigate these disparities (Banzhaf et al., 2019). Addressing these disparities calls for creative strategies to build capacity for transformative change and help fundamentally change this underlying generative framework (Castán Broto et al., 2022). Procedural justice refers to rethinking processes and improve the involvement of marginalized groups in decision-making, which in turn helps address present-day inequities (Banzhaf et al., 2019; Walker & Day, 2012). Priorities and approaches to elevate the voice of marginalized groups can help better inform urban development and in turn help fundamentally restructure our approaches to make cities more inclusive and accessible (Reuter, 2019). The higher cost burden for basic necessities on low income households is not just an observed inequality, and is better termed as a distributional *injustice* (Moore & Webb, 2022). Energy burden for example is also linked to these historical patterns of racial discrimination, and contributes to disparate wealth gaps between racial groups (Chen et al., 2022; Walker & Day, 2012). Households that are more vulnerable are more likely to live in substandard housing and have fewer means by which to improve its condition or address energy inefficiencies (Walker & Day, 2012). Inadequate or poor-quality housing have historically exacerbated the spread of disease, have influence over both physical and mental health, and contribute to increased mortality (Palacios et al., 2021), which helps focus this analysis to examine the influence of the built environment on health outcomes. Disadvantaged neighborhood conditions are widely acknowledged to contribute to poorer health outcomes (Boch et al., 2020), and as such are important components to better understanding the complex social factors that influence wellbeing. It is of particular interest in this study to investigate relationships between substandard and cost-burdened housing situations and how this might predict poor health outcomes.

Housing quality influences physical and mental health, which occurs both through direct and indirect means (Bentley et al., 2012; Bonnefoy, 2007). Direct pathways of influence on health can include factors such as temperature regulation, dampness, and indoor air quality, while indirect influences can include housing affordability stress, neighborhood safety, and housing tenure (Bentley et al., 2012; Bonnefoy, 2007; Pevalin et al., 2017). Disparities in housing conditions can manifest as both structural (i.e. poorly insulated spaces are more difficult to keep temperature regulated) and cost-burdened manners (i.e. high utility costs resulting from poorly insulated spaces), and reveal opportunities to investigate how these types of challenges influence health. The collective influence of these factors on health is well established in the literature as *social determinants of health* (SDOH) which help create a more comprehensive picture of how ones health is determined (Stacy et al., 2019; Telfar Barnard et al., 2020). For example, those children that have experienced eviction (either formally through court action or informally through forced or involuntary moves) are more likely to face disciplinary action in school and have more involvement with the criminal justice system as adults (Hatch & Yun, 2021). The complex associations between housing instability and social outcomes speaks to the need for further research to elucidate how housing quality issues manifest in one's wellbeing. Research exploring factors that influence health can help inform public sector service delivery improvements and local policy, and these types of neighborhood-level approaches should be considered in improving residents well-being (Stacy et al., 2019).

Although it is well established that living conditions influence social, physical, and mental well-being, the causal mechanisms still remain challenging to ascertain (Boch et al., 2020; Bonnefoy, 2007). Longitudinal data analysis that emerges from observation studies is one potential tool in establishing causal relationships, especially when randomized control trials are not possible (Singh et al., 2019). Given that exposure to poor housing conditions can have cumulative impacts on mental health, and past experience with poor housing has lasting impacts even years later on one's mental health (Pevalin et al., 2017), longitudinal studies may help better elucidate these causal factors influencing health outcomes. Evidence of negative relationships between mental health and poor housing affordability for example was reported using longitudinal data by Bentley et al. (2012), demonstrating that poor *conditions* are not the only consideration in housing-related stressors. In examining a stratified sample of over 50,000 housing units, Boch et al. (2020) found that each additional poor housing condition measure was associated with poorer health status and higher rates of hospitalization than those that do not experience poor housing conditions. Despite this cross-sectional analysis lacking causal implications, the results point to the need for policy interventions that help improve access to quality housing for those most at risk.

Research Design and Methods

This study will employ both quantitative and qualitative components to incorporate a mixed methods design. This study will first use publicly available datasets to explore the associations between (a) poor housing conditions and incidences of poor mental health and (b) high energy burden and incidences of poor mental health in Memphis and Shelby County, TN. Through trends analysis between these pairs of variables we can begin to examine in more detail the patterns and relationships between housing conditions and health outcomes, and control for other potential variables available at the census tract level including percent low to moderate-income, percent with college education or above, percent of non-white, percent of pre-1978 housing stock, and percent without health insurance. Triangulation will then be used to compare and analyze both the qualitative and quantitative data collected in this study, which allows a more comprehensive picture to emerge than if a single source of data were used that may help eliminate or reduce potential sources of bias (Heale & Forbes, 2013). Tracking energy burden from clients receiving home rehabilitation interventions will help augment this study and serve to quantify tangible, real impacts to community members. It is also of note that triangulation comes with the burden of time-intensive strategies and potential disharmony or conflict in results from data analysis (Thurmond, 2001). Despite the drawbacks and challenges, this approach is widely acknowledged to lend a more thorough analysis of the issues of interest to a researcher (Heale & Forbes, 2013; Thurmond, 2001), and as such will be employed in this study design to explore the relationships between mental health, energy burden, and housing conditions.

Ordinary least squares (OLS) regression can also be used to analyze how predictors influence a response variable (Moore & Webb, 2022), in this case how housing quality and cost burdens predict mental health outcomes. Additional regression analyses that include multinomial logistic regression and models that address spatial components (such as Geographically Weighted Regression (GWR)) will also be incorporated into this analysis to better capture how the dependent variable of mental health outcomes is influenced by independent variables such as environmental factors including housing condition, eviction experience, or energy burden.

Publicly available datasets will comprise the bulk of data collection for this study and will then be augmented using actual client utility data from Shelby County's home rehabilitation program. Incidences of poor mental health (crude prevalence) for each census tract in Memphis will be used as reported through the CDC 500 Cities Project (*PLACES: Local Data for Better Health | CDC*, n.d.). Poor housing conditions for each census tract in Memphis will be used as reported through the US Census Bureau and US Department of Housing and Urban Development's 2021 American Housing Survey and local tax assessor data to corroborate aggregated AHS data (*American Housing Survey (AHS) - AHS Table Creator*, n.d.; *Assessor of Property, Shelby County TN*, n.d.). Energy burden data for each census tract will be extracted from the Low-income Energy Affordability Data (LEAD) Tool through the Department of Energy, the most recent data showing 2018 values (*LEAD Tool*, n.d.). Other socioeconomic variables that are relevant to this analysis and available at the census tract level and available through the American Community Survey's (ACS) 2021 1-year estimates data will be included in the model in order to control for other factors including percent low to moderate-income, percent with college education or above, percent of non-white, percent of pre-1978 housing stock, and percent without health insurance. Pre-1978 homes are a useful proxy to include given that lead-based paint was used up until this time, and those living in homes older than 1978 are more exposed to lead hazards than those living in newer homes. Future analyses can incorporate lead-based paint hazards and risk of elevated blood lead levels in children for additional health outcome investigation. Taken together, the above listed independent variables will help control for other factors that may influence our response or dependent variable (in this case incidences of poor mental health). It is hypothesized that a positive association will emerge from this analysis in that a census tract with greater frequency of housing problems and higher cost burden will also be more likely to have higher incidences of poor mental health.

Table 1. Data sources and respective variables detailed from each database[1].

Data Source	**Variables**	**Variable Codes and Categories**
PLACES 500 Cities Project – Data available at census tract level	Incidences of poor mental health (equivalent to depression rates as labelled in dataset)	MHLTH_CrudePrev variable codes are numerical counts of incidences of poor mental health, crude prevalence, for each census tract.
AHS 2021 – Data available	ADEQUACY (equivalent to housing problems); UPKEEP	ADEQUACY variable codes include ||1: Adequate, ||2: Moderately inadequate, ||3: Severely inadequate. UPKEEP variable codes

[1] Acronyms are as follows: MHLTH_CrudePrev = Mental health crude prevalence; AHS = American Housing Survey; DBUTBILL = Delinquency rates for utility bill payments; ACS = American Community Survey; ELEP = Electricity expenditure in dollars per year; GASP = Gas expenditure in dollars per year; HINCP = Household income; AMI = Area Median Income; LEAD = Low-income energy affordability data.

at metro level for each census tract	(another measurement of housing issues); DBUTBILL (Delinquency in utility bills)	include ||1: Less than 3 upkeep problems ||2: 3 or 4 upkeep problems ||3: 5 or more upkeep problems. DBUTBILL variable codes include: ||1: Received notice, utilities shut off||2: Received notice, utilities not shut off||3: Received notice, shut-off not reported||4: No notice||M or -9: Not reported||N or -6: Not applicable
ACS 2021 – 1 year estimates	Percent low to moderate-income; percent with college education or above; percent of non-white; percent of pre-1978 housing stock; percent without health insurance	All variables are percentage of individuals or households in each census tract (range 0-100%) for each census tract.
LEAD Tool Data – 2018 AMI	Average energy burden as a percentage of total income, using variables ELEP (electric costs), GASP (gas costs), and HINCP (average household income) from the LEAD database	ELEP variable is the Calibrated ACS average household annual electricity expenditure ($/year); GASP variable is the Calibrated ACS average household annual gas expenditure ($/year); HINCP variable is the average annual household income ($/year).

Data will be manually examined, and outliers will be removed prior to analysis given that modelled data (such as CDC's 500 Cities Project) are subject to numerical modeling errors that could skew the results. All data points removed (negative values and values above a certain percentage of the average, for example) will be detailed in the final report. Data sets will be matched using vlookup functionality in Microsoft Excel by the census tract Federal Information Processing Standards (FIPS) code. A scatterplot will be used to first show trends between (a) poor housing conditions and incidences of poor mental health and (b) high energy burden and incidences of poor mental health and correlation coefficients will be reported. Note that these associations will reveal correlations, and no causal factors can be assigned.

In addition, ordinary least squares (OLS) regression will allow more in-depth analysis incorporating other explanatory factors related to the relationship between housing quality issues and mental health outcomes. As an example, Pevalin et al. (2017) utilized pooled OLS regression to test whether those exposed to a greater number of housing problems have poorer mental health than those that experienced fewer while controlling for other factors that may also influence mental health. This technique allows for the inclusion of other explanatory variables and confounding factors to be incorporated into the model including tenure type, marital status, and financial strain, thereby controlling for these factors and allowing more rigorous statistical analysis of the variables of interest. OLS allows for an analysis to explore the relationship between predictors and a response variable (Moore & Webb, 2022), in this case mental health outcomes serve as the dependent variable. However, a conventional OLS model may reveal biased and inefficient coefficients if data are not randomly distributed, as is the case with energy burden, for example (Chen et al., 2022). To address this spatial heterogeneity, Chen et al. (2022) utilized four different models for energy burden analysis that first capture traditional OLS techniques but also include spatial regression models that greatly improved their predictive capacity. Other models including geographically weighted regression (GWR) and multiscale geographically weighted regression (MGWR) can also be used in to predict an outcome variable and should be considered beyond non-spatial models (Moore & Webb, 2022). In future expansions of this work this proposed study can incorporate additional variables into OLS regression *and* spatial regression models including GWR and MGWR to better explain associations between variables and control for other potentially influential factors.

Qualitative reviews and quantitative counts from interview data will also be utilized in this study to help identify themes and personal experience around housing quality issues and impacts on health. Qualitative work was identified as a key factor to make progress in better exploring the indirect impacts of housing-related stressors on health outcomes (Bentley et al., 2012), helping validate the integration of this strategy in the current proposed project. In a systematic review of housing disadvantage and mental health, Singh et al. (2019) identified terms used to capture or measure both (a) *housing disadvantage* and (b) *adverse mental health* including (a) mortgage delinquency, housing mobility, tenure, evictions, physical conditions, and (b) depression, anxiety, mental strain, allostatic load and psychological health. Table 2 bases the textual review on Singh et al. (2019) but modifies it to outline verbiage and themes this analysis will use to count and identify in interview transcripts. It is hypothesized that a positive association between these variables will emerge. If an individual reports housing disadvantage indicators, they are also more likely to also report one or more adverse mental health indicators, as also reported in Pevalin et al. (2017). Each individual transcript with be analyzed with the search terms and interpretations (indirect references will qualify as positive counts) of housing disadvantage measures and adverse mental health indicators (Table 2). Narratives and interpretation will also take place in order to capture a more personalized representation of lived experiences. Note that adverse mental health indicators are treated as a binary (yes/no) rather than categorical (none, mild, severe) variable to better align with the regression models utilized in this study.

Recruitment for participants will occur through local neighborhood groups and Community Development Corporations (CDCs), as well as from housing programs operated by the City of Memphis and Shelby County Government. Through a two-year study period, the research team will incorporate interviews from all areas of the county and aim to include representatives from each census tract given the need to corroborate modeled data with personalized narratives at the same scale. All personally-identifiable data will be anonymized prior to inclusion in the final manuscript, with only a category (rehabilitation program participant, renter participating in City supportive services program, or similar designation) description to give context to responses.

Table 2. Textual and thematic analysis of interview data will count the incidences of each of the following measures for both (a) housing quality and (b) mental health indicators (Singh et al., 2019) [2]

A. Housing Disadvantage Measures	B. Adverse Mental Health Indicators

[2] Table 1 additional narrative: Note rows in columns A and B are unrelated. Absolute counts of incidences serve as data collection measures to report total housing quality issues and total mental health indicators.

Physical housing conditions are compromised (includes leaks, temperature regulation or insulation issues, draftiness, mold, and similar)	Depression frequency and severity (self-reported assessment of depression tendencies)
Tenure (renter/homeowner status)	Anxiety frequency and severity (self-reported assessment of any resident feeling anxious or
Mobility (number of moves in past year, average length of stay in recent homes)	Mental strain (any self-reported stress or frustration around housing or health-related issues)
Evictions (past experience with eviction and number of evictions in one's history)	Allostatic load (reported difficulty coping with the compounded stress of living circumstances)
Payment delinquency (number of times rent or mortgage went unpaid or only partially paid in the past year)	Psychological health (any self-reported psychological challenges not otherwise captured in other analysis categories)
Overcrowding and/or transient roommates (number of occupants per room and/or number of past transient or part time roommates)	Emotional distress (any self-reported difficulties that lead to feelings of overwhelmed, frustrated, or otherwise compromised emotional states)
Energy burden (proportion of income spent on utility costs)	Financial stress (self-reported stressors related to limited income, ongoing housing and utility costs, and other evidence of financial compromises or limitations)

Table 3. Anonymized frequency of housing disadvantage measures and adverse mental health indicators reporting summary. Data forthcoming in future analyses. Note third parties such as policy makers and legal counsel will report anecdotal evidence of their client experience rather than first-hand experiences and will be reported accordingly.

Individual	# of housing disadvantage indicators	Summary of which indicators	# of adverse mental health indicators	Summary of which indicators
A – rehabilitation program participants				
B – renters receiving rental program support				

C – homeowners seeking mental health services				
D – local policy officials				
E – homeowner receiving healthy homes services				
F – legal counsel or litigation support official				

Energy burden data will be collected from clients undergoing housing rehabilitation or lead hazard reduction projects through the Shelby County Department of Housing. Utility bills will be collected through coordination with Division of Community Services for access to all Memphis, Light, Gas and Water (MLGW) utility bills following participant consent. Twelve months of utility bill data both pre- and post-intervention will control for seasonality changes. Data will be normalized using average daily temperature to account for between-season differences. Energy burden as a percentage of income will be calculated for total bill amount, gas usage, and electricity usage in order to compare utility cost changes with installed equipment.

Challenges around obtaining clean, accurate data are notable in this field of study. Large data sets with standardized assessments of housing conditions alongside health outcomes are difficult or more generally unavailable, lending even greater challenges to this type of research (Palacios et al., 2021). There are also no standardized definitions of what constitutes 'healthy housing' which makes coded or reliable data difficult to find and analyze (Bonnefoy, 2007). This study aims to conduct small-scale and locally relevant assessments to begin contributing to the narrative around housing conditions and associated health outcomes in Memphis and Shelby County, TN. This work serves as an initial step to uncover associations between housing condition and mental health and will incorporate mixed methods to better capture both a county-wide quantitative picture while also bringing in a more personalized lived experience into the analysis. This approach in using multiple methods is a form of triangulation that helps to more comprehensively explore the topic and offers opportunity to more thoughtfully analyze the phenomena in question (Thurmond, 2001).

In future analyses, longitudinal data can be collected from existing housing rehabilitation initiatives in Memphis and Shelby County, TN. A quasi-experimental design or randomized control trial would help better capture cause and effect of how interventions influence health outcomes (Palacios et al., 2021), and can help identify how specific interventions relate to health variables of interest including energy burden relief and associated financial impacts. The proposed study helps identify potential variables of interest and subsequent influence on health through both non-spatial and spatial regression models and can be used to help inform future experimental work. These analyses can then be used to help inform policy and service delivery in the public sector and help cities incorporate more rigorous data-driven decisions into government operations (Moore & Webb, 2022).

Conclusions

Going beyond cross sectional or point in time analyses of poor housing conditions and impact on health outcomes, Pevalin et al. (2017) identify the importance of long term exposures to these conditions as a factor in one's mental health. An extension to this proposed study could involve a longitudinal analysis of clients and a comparison of how long-term exposure to poor housing quality impacts local residents in Memphis and Shelby County, TN and expand our use of this evidence to better inform policy and programmatic shifts. Further, analyzing how intentional policy interventions such as the strategic code enforcement and health impact assessments in Memphis, TN highlighted in Stacy et al. (2019) demonstrate how non-health policies and programs could benefit from public-health sector input. Given that adolescents that were subject to instable housing situations are more likely to experience depression (Hatch & Yun, 2021), it becomes important to describe and quantify the factors leading to poor mental health. This study helps bring clarity to these issues through first analyzing existing data and second applying it to the policy space in supporting the incorporation of more actionable knowledge in government programming. Improved coordination between public health and community and economic development agencies would help bridge current policy divides and help facilitate coordinated efforts for improved community health outcomes (Bonnefoy, 2007; Singh et al., 2019; Stacy et al., 2019).

Actionable Steps for Impact

Given the complex nature of social determinants of health and the multiple factors that influence health and well-being, policymakers should take care to incorporate health-focused initiatives in policy. Policy objectives have not done enough to address social, environmental, or economic inequities, and in order to pursue a more just city more intentional effort is required by policy makers and decision-makers (Perry & Atherton, 2017). One strategy to address this environmental justice issue is to make more intentional effort to include diverse voices in decision-making and policy circles (Banzhaf et al., 2019). Going further, analyses to explore the relationships between environmental factors and health can help identify specific strategies to change and improve local policies and intervention strategies. The negative and long-term impacts from evictions for example is evidence to pursue improved coalition-building and policy design centered on health, and can take the form of right-to-counsel for evictions cases and subsequent evaluation of antieviction policies (Hatch & Yun, 2021).

Policies related to the built environment and infrastructure including land use, zoning, housing, and transportation networks can help mediate these types of social justice outcomes (Maxim & Grubert, 2022), providing insight into how policies can have tangible and meaningful impact. There are active policy discussions, for example, to support federal allocations to address housing specifically, which would help address the disproportionate burden on low income and minority households that are occupying substandard, inefficient housing (Maxim & Grubert, 2022). It becomes important to examine these types of distributional injustices to help inform how policy interventions can address longstanding social issues (Walker & Day, 2012).

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