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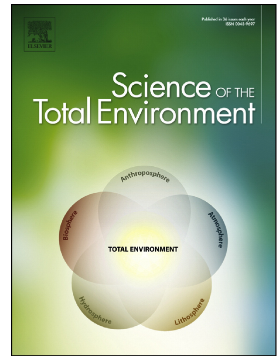

Energy burden and mental health: A national study in the United States

Soojin Han, Ming Hu, Xue Gao, Youqin Huang, Fei Guo, Gordon Shen, Donggen WANG, Shao Lin, Kai Zhang

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Energy Burden and Mental Health:
A National Study in the United States

Authors

Soojin Han
Department of Sociology
University at Albany, State University of New York
Albany, NY, USA
shan6@albany.edu

Ming Hu
School of Architecture
University of Notre Dame
South Bend, IN USA
mhu1@nd.edu

Xue Gao
Askew School of Public Administration and Policy
Florida State University
Tallahassee, FL, USA
xg23d@fsu.edu

Youqin Huang
Department of Geography and Planning,
University at Albany, State University of New York,
Albany, NY USA
yhuang@albany.edu

Fei Guo
International Institute for Applied Systems Analysis (IIASA),
Schlossplatz, Laxenburg, Austria
guof@iiasa.ac.at

Gordon Shen
Department of Management, Policy, and Community Health, School of Public Health
The University of Texas Health Science Center at Houston,
Houston, TX USA
Gordon.C.Shen@uth.tmc.edu

Donggen WANG,
Department of Geography,

Hong Kong Baptist University
Kowloon, Hong Kong
dgwang@hkbu.edu.hk

Shao Lin
Department of Environmental Health Sciences, School of Public Health
University at Albany, State University of New York
Rensselaer, NY USA
slin@albany.edu

Kai Zhang
Department of Environmental Health Sciences, School of Public Health
University at Albany, State University of New York
Rensselaer, NY USA
kzhang9@albany.edu

Corresponding authors:
Kai Zhang
Department of Environmental Health Sciences, School of Public Health
University at Albany, State University of New York, Rensselaer, NY USA 12144
Telephone: 518-473-1821 | E-mail address: kzhang9@albany.edu

Ming Hu
School of Architecture, University of Notre Dame, South Bend, IN USA
Email: mhu1@nd.edu

Abstract

The prevalence of mental health issues in the US has significantly risen over the past decade, and it is presumably linked to an energy burden issue that has recently gained attention as a critical social determinant of mental health. Utilizing extensive nationwide datasets at the census tract, we found that the census tract level energy burden is positively associated with two key mental health indicators even after accounting for living, housing, and sociodemographic characteristics: the prevalence of frequent mental distress and physician-diagnosed depression, across all US urban areas. We also observe that these associations are consistent across various climate regions. The findings highlight that energy burden has a detrimental impact on mental health, and that it should be e considered a significant social determinant of health in future studies. Lastly, our study advocates for national policies to achieve energy justice and address disparities in mental health.

Keywords: energy burden, mental health, depression, mental distress

Introduction

Over the past ten years, there has been a significant increase in the prevalence of mental health illness in the United States, rising 18.1% in 2010 to 22.8 % in 2019 of adults reporting that they experienced mental health issues within the past year (National Institute of Mental Health, 2023). More notably, individuals with incomes below the poverty line had a significantly higher rate of mental health problems, nearly seven times more compared to those with incomes at or above 400% of the poverty line (Jitender Sareen et al., 2011). Among social determinants of mental health, the concept of energy burden is beginning to receive great attention as a crucial link to public health (Churchill & Smyth, 2020; Hernández, 2016; Hernández & Siegel, 2019; Lin & Okyere, 2020). Energy burden refers to the inability of a household to afford sufficient energy sources for basic needs such as heating, cooling, cooking, cleaning, lighting, and using electrical appliances, which has become a common problem in US households today (Hernández, 2016; Jessel et al., 2019). Energy Information Administration (EIA) recently reported that approximately 31% of U.S. households experienced challenges in paying energy bills or maintaining adequate heating or cooling in homes[7]. Given that residential energy plays a vital role in sustaining individuals' lives, the uneven distribution of energy burden across different social demographic groups can be a consequential contributor to health inequalities in the United States (Hernández, 2016).

Even though the United States presents a unique context for examining the impact of energy burden on the population's mental health, to date, there is a notable absence of studies have investigated the relationship between these two phenomena in the United State. Unlike in developing countries, where energy issues are often driven by a lack of modern energy service markets or accessibility of modern energy sources, the energy burden in the US is largely associated with by socioeconomic factors and diverse geographic conditions(Li et al., 2022; Lin & Okyere, 2020; Sy & Mokaddem, 2022; Wang et al., 2021; D. Zhang et al., 2019; J. Zhang et al., 2022). For example, while average energy expenditure for US households in 2019 was approximately 3.8%, US households with incomes equal to or below 200 percent of the federal poverty line allocate 8.1 percent of their incomes on energy expenses (Drehobl et al., 2020). Similarly, low-income and racially minority households in the United States tend to consume even more energy per square foot compared to affluent and white households. Households with children or black and Hispanic households faced higher odds of receiving a notice or experiencing disconnection from the utility service and bill payment challenges in 2019 and 2020 (Memmott et al., 2021). Those findings suggest that energy burden is not merely a consequence of rising electricity prices but should be considered an underappreciated social determinant of health in the United States (Hernández, 2023). From this perspective, it is crucial to explore whether it is associated with the current significant mental health issue and to what extent if affects the prevalence of mental health outcomes in the United States.

Moreover, the US encompasses a wide range of geographical and climate conditions, from the extreme heat of the Southwest to the cold of the Northern states. This variation results in diverse residential energy needs and potentially corresponding impacts on mental health outcomes (Auffhammer & Mansur, 2014; Maxim & Grubert, 2022). Considering that the prevalence of mental health outcomes is related to climate conditions and needs for residential energy needs, research in the United States provides empirical evidence of the relationship between energy burden and mental health outcomes for policymakers.

Along with the climate regions, to explain the relationship between energy burden and mental health, the current study also considers housing characteristics and living conditions that are well known to be important to mental health outcomes. It has been found that housing characteristics, such as age and construction materials of housing unit or housing density are associated mental health (Newman, 2001; Singh et al., 2019). However, to our knowledge, no previous empirical research has taken those factors into account in exploring the relationship between energy burden and mental health across the United States. By considering a range of housing, living and sociodemographic factors that are known to be important to mental health, our study can contribute the existing literature by providing a more comprehensive understanding of the topic.

To bridge the existing literature gaps, our study ventures beyond prior investigations by comprehensively analyzing all census tracts with low-income families across the United States. Notably, our study incorporates a wide range of established census- and county-level data sources to account for factors related to mental health, such as demographic characteristics as well as living and housing characteristics that have not been examined in the previous study. For this goal, we utilized the 2019 CDC PLACES data in conjunction with American Community Survey and other multiple datasets. Additionally, we stratify the models by climate zones, allowing us to investigate how the relationship between energy burden and mental health outcomes varies across different climate zones. In essence, our study makes a valuable contribution to the existing literature on energy burden by offering the initial evidence on the relationship between energy burden and population mental health nationwide in the United States.

1.1 Existing Literature on energy burden and mental health

Although existing studies on energy burden and mental health focused on different geographic regions and population, many of them have found that energy burden has a negative effect on mental health. Along with the backdrop of the global energy crisis, many of existing studies have highlighted energy burden and its impact on health across European countries. A comparative study of 32 European countries found that a higher proportion of energy-poor populations is linked to poorer emotional well-being and a greater likelihood of depression, especially in more egalitarian societies like Sweden and Slovenia (Thomson et al., 2017). Another study involving 27 European countries provided further evidence that individuals unable to afford adequate heating or who had utility bill arrears were more likely to report poor health and depression (Oliveras et al., 2021). The positive relationships observed in the European studies suggest it may have a similar dynamic in the United States.

Recognizing the financial strain associated with energy burden, recent studies have explored the relationship between energy burden and mental health among vulnerable populations, such as pregnant women and older adults. For example, in Australia, the consecutive inability to afford home heating increased the odds of depressive symptoms by 1.95 times (Bentley et al., 2023). Similarly, a study in Ireland focusing on vulnerable populations revealed that energy burden is associated with a 1.64-fold increase in the odds of maternal depression (Mohan, 2021). Another recent study on China found that energy burden exerts cumulative effects on mental health outcomes and cognitive health of older adults in China, as evidenced through self-rated health (Li et al., 2022). Those findings suggest that energy burden may induce financial stress, which could contribute to the deterioration of mental health.

Economic strains, particularly among low-income households, exacerbate mental health risks due to the significant portion of income allocated to energy needs. This financial strain leaves fewer resources for other essential needs, potentially leading to adverse mental health outcomes (Bhattacharya et al., 2003; Burlinson et al., 2022). Research using in-depth interviews illustrated a detailed context for the financial hardship associated with energy costs. According to the qualitative studies from the US and Canada, the study participants reported that they dreaded utility bills coming cue and there were usually the fear of utility service disconnection due to late or nonpayment Participants emphasized that these experiences of anxiety and stress in daily life significantly worsened their mental health (De Haro & Koslowski, 2013; Harrington et al., 2005; Hernández, 2016).

The association between energy burden and mental health can be different depending on the climate conditions. However, to our knowledge, few studies take into account climate regions in studying the impact of energy burden on health. Extreme weather events can cause stress, anxiety and trauma, particularly for vulnerable populations who spend more time at home and low-income families who often face lack of adequate heating or cooling in their homes. Empirical research on indoor temperature and mental health have shown that being cold at home and damp housing increase psychological vulnerabilities and contribute to a variety of mental well-beings such as persistent worry about affordability, anxiety, cold-induced stress, feeling loss of emotional control and depressive symptoms (Liddell & Guiney, 2015; Liddell & Morris, 2010; O'neill et al., 2006; Riva et al., 2023). During the extreme weather conditions, low income families are more likely to experience fuel shortage, energy service interruptions, power outrage, which can exacerbate existing health conditions, increase the risks for developing diseases, ultimately impacting their mental health in a long run (Jessel et al., 2019). Although these studies did not specifically examine how varying energy burdens are associated with mental health across different climate regions, they suggest that the impact of energy burden on mental health may vary by region.

2. Materials and Methods

First, in this population-based study, we utilized census tract level information to measure the neighborhood. Before introducing the datasets used for the study, it is worth mentioning several reasons why a census tract is an appropriate unit of analysis for understanding the population mental health in relation to energy burden. First, a large body of literature on neighborhood effects on health has suggested that various census tract level characteristics are associated with population-level health outcomes (Arcaya et al., 2016). Second, census tracts are preferred "small area" geographical units for data analytics to represent local socioeconomic conditions, as well as the useful administrative unit used by federal, state, and local governments (Printing Office, U.S. Government, 2019). Thus, results from census tract level analysis can produce meaningful population health policy implications for energy burdended neighborhoods. Third, the census tract is the smallest geographic unit in which data on key measures of this study are available in the United States.

2.1. Data

In this study, for the purpose of developing comprehensive metrics pertaining to health, energy, living, housing, and socio-demographic characteristics, we incorporated data from five distinct datasets, as detailed below.

First, for the health measure this paper used 2019 PLACES: Local Data for Better Health released by Centers for Disease Control and Prevention (CDC). The data provide model-based 29 chronic disease measures at multiple local area-levels (county-, place-, census tract – and ZCTA level) across 500 largest American cities based on the Behavioral Risk Factor Surveillance System (BRFSS). The data include approximately 28,000 census tracts among 500 cities whose population is ranged from approximately 43,000 in Burlington, Vermont, to 8,300,000 in New York City, New York as of 2019 (Bureau, 2019).

Second, for the energy measure, this paper used 2018 Low-Income Energy Affordability (LEAD) data. LEAD, available from U.S. Department of Energy, compile information of housing units, monthly expenditures on housing energy use including electricity, gas, and other fuel and household income at Census tract levels(Ma et al., 2019). The estimates of residential energy use and energy burden are tabulated based on 2018 5-year American Community Survey.

Other energy related data and information of housing conditions were drawn from 2016-2020 Picture of Subsidized Housing (PSH) and 2018 End-Use Saving Shapes. PSH, provided by U.S. Department of Housing and Urban Development includes the nearly 5.1 million US households receiving housing assistant programs from the Department of Housing and Urban Development every year and collects the information of the assisted households and their residents' characteristics at the national, state, city, CBSA, and Census tract level. To make the study period consistency, we combined the census tract level data from each of the individual year years (2016, 2017, 2018, 2019 and 2020) and tabulated the 5-year estimate data for our analysis. 2018 End-Use Saving Shapes is used for the study as they profile energy efficiency and electrification of the U.S. residential building stocks. Since the unit of analysis of the data is individual buildings, not a geographic unit, they needed to be summarized at the geographic level for the analysis. By using the address information of each building, we calculated the percentage and counts of geometry wall, cooling system, heating system types, roof insulation status of the residential buildings by every county – smallest geographical unit available in the address information – across the United States.

For socio-demographic measures, this study used 5-Year estimates of 2015-2019 American Community Survey (ACS). The ACS participation is mandatory, and the survey contains broad information on social, economic, and demographic characteristics. The primary advantage of using the ACS 5-year estimates is that the data are available for all geographical units down to the block level group and provide high reliability of the data for less populated areas. For consistency of the unit of analysis, we used census tract level measures of the ACS.

Lastly, to account for climate zones since climate related stressor created by outdoor and indoor temperature is one of possible causes of chronic kidney disease, this paper used International Energy Conservation Code (IECC) (Johnson et al., 2019). While IECC originally aims at evaluating energy efficiency of residential and commercial buildings and providing specific requirements for the energy related performance tailored to different climate zones, this study utilized the measure of climate zones from the IECC.

2.2.Measures

2.2.1. Outcome variables

In this study we used two different measures of mental health. The first outcome variable of the study is census tract-level crude prevalence of having frequent mental distress obtained from CDC PLACES data. The measure is based on the percentage of respondents aged 18 years old or older who reported 14 or more days during the past 30 days during which their mental health was *not* good. Another outcome variable we explore is census tract level crude prevalence of physician-diagnosed depression obtained from CDC PLACES data as well. The measure is based on the percentage of respondents aged 18 years old or older who reported that they had been told by a doctor, nurse, or other health professionals that they had a depressive disorder.

The two outcome variables were constructed by CDC using BRFSS data and a Multilevel Regression with Poststratification (MRP) approach to estimate the small area level (here, census tracts) estimates. Both estimates were age-, sex-, race/ethnicity-, county level federal poverty adjusted (Division of Population Health, National Center for Chronic Disease Prevention and Health Promotion, n.d.; Greenlund et al., 2022; X. Zhang et al., 2014).

2.2.2. Focal Explanatory variable

The focal independent variable of the study is the census-level energy burden that is measured as the averaged percentage of annual energy expenditure out of the energy of annual income.

2.2.3. Covariates

First, we included several census tract-level living and housing conditions in our analysis. We included the average utility allowance among households in dollars per month measured in dollars per month. This estimate reflects the utilities covered by the upper limit of government subsidies provided to the low-income households to assist with their utility expenses. We also included the percentage of crowded housing and median ages of building. The crowdedness is measured through the share of houses in a census tract that have number of residents exceed the number of bedrooms in a house. For the median age of buildings in a census tract, the median age was calculated by subtracting the median year of construction from 2019. We imputed the original value of 0 for the median year of houses built with 1939, the presumably the oldest possible value that could have been reported in the Census as of the survey year. We also included the percentages of houses using gas, electricity and other fuel types respectively. In addition to the census tract level housing characteristics, due to the availability of data, county level housing characteristics are also included in the study. The housing characteristics used were physical wall type, the percentage of houses equipped cooling, heating systems and the percentage of houses with roof insulation.

Second, we adjust for the census tract level social and demographics. Detailed covariates are as follows: percentage of females in a census tract, percentage of nonwhites in a census tract, percentage of the population who are 65 or over, percentage of the population age 25 and older whose educational attainment is less than high school, the unemployment rate, and the median household income in a census tract. For the percentage of nonwhites, it included non-Hispanic blacks, non-Hispanic Asians, American Indian/Alaskan Native (AIAN), Native Hawaiian and Pacific Islanders, and Hispanics. For all covariates included, we used 0.7 as a threshold to decide the covariates for the model.

Lastly, this study considered climate zones. Climate zones were measured based on International Energy Conservation Code (IECC). The IECC is originally comprised of nine climate zones (extremely hot, very hot, hot, warm, mixed, cool, cold, very cold, and subarctic/arctic) and marine, dry, and moist status of each climate zone and identifies the entire US territory as 19 climate zones. However, due to the sample limitation, we reduce the climate zone categories into five: very hot and hot, warm, mixed, cool, cold and very cold).

2.3.Statistical analysis

To examine the association between energy burden and the prevalence of health outcomes – having frequent mental distress and depression – we used multilevel random intercept regression models that can allow us to account for the variability at the city level. Since census tracts are nested in a city and shared similar characteristics, meaning that the data have a multilevel structure, we implement a random intercept model, treating the level-1 intercepts vary by cities (Raudenbush & Bryk, 2002). To guide the selection of the appropriate multilevel model and the covariance structure, we calculate ICC and use likelihood-ratio tests. Results suggest that incorporating a random intercept for cities explains the data better in both models for the prevalence of frequent mental distress and depression. Accordingly, our general specification is shown as follow:

$$Y_{ij} = \gamma_{00} + \beta_1 X_{1ij} + \sum_{k\geq 2} \beta_k X_{kij} + u_j + e_{ij},$$

where Y_{ij} is 1) the crude prevalence of frequent mental distress (among adults ≥18);

2) the crude prevalence of physician diagnosed depression (among adults ≥18) in the i-th census tract in j-th city,

γ_{00} is the average intercept across all census tracts, representing the average value of the outcome variable when all predictors are zero,

$\beta_1 X_{1ij}$ is the effect of high energy burden on the prevalence of chronic kidney disease,

$\sum_{k\geq 2} \beta_k X_{kij}$ is the sum of the effect of the covariates on the prevalence of chronic kidney disease,

u_j *is the random intercept associated with j-th city, representing the variability in the prevalence of kidney disease that is attributable to differences between cities and capturing the influence of city-specific characteristics on the prevalence kidney disease,*

e_{ij} *is the residual error term for i-th census tract within j-th city.*

Furthermore, in order to explain whether the association between energy burden and the prevalence of mental health problems and depression differ by climate zones in the United States, we employ the stratified analysis by conducting the same models by five climate zones based on the IECC climate zone.

3. Results

3.1. Overview of sample characteristics of the study

[Table 1] is about here.

The sample is restricted to 25,643 census tracts spanning in 481 cities across 46 states and the District of Columbia. It focuses on low-income households and excludes census tracts in New Jersey in terms of 2019 CDC PLACES data, as well as Alaska and Hawaii from the 2018 End-Use Savings Shapes. Descriptive characteristics of the sample, as stratified by climate zones based on the International Energy Conservation Code and the American Society of Heating, Refrigeration, and Air- Conditioning Engineers specification (very hot and hot, warm, mixed, cool, and cold and very cold climate zone), are shown in Table 1.

This study focuses on two mental health outcomes. The first outcome is the average crude prevalence of frequent mental distress which was measured through the percentage of respondents aged 18 years old or older who reported 14 or more days during the past 30 days during which their mental health was *not* good(Cree et al., 2020). The other outcome is the census tract-level crude prevalence of depression that is based on the percentage of respondents aged 18 years old or older who reported that they had been told by a doctor, nurse, or other health professionals that they had a depressive disorder.

As shown in Table 1, the prevalence of frequent mental distress among adults exceeds the national level in both very and hot and cool regions, while it remains comparatively lower in warm and cold and very cold regions. Conversely, the prevalence of depression among adults displays distinct regional patterns. It peaked in cold and very cold regions and mixed climate regions.

In terms of energy burden, U.S. households in urban areas spent approximately 3.024% of their annual income on energy expenses. Households in census tracts located in very hot, hot, and cool climate regions spent more than the national average, with percentages of 3.142 and 3.566% while those in warm, very cold, and cold climate regions spent less, with percentages of 2.545% and 2.717%, respectively. These findings indicate a regional variation in energy burden, with certain climate conditions necessitating higher energy expenditures.

3.2.Census tract level energy burden and frequent mental distress

We examined an investigation into the direct relationship between energy burden at the census tract level age-adjusted crude prevalence of having frequent mental distress and physician-diagnosed depression, among adults (aged 18 and older), respectively. This inquiry was carried out employing a multilevel random intercept regression analysis. We included energy burden, our primary independent variable, and housing and living characteristics and socio-demographic characteristics as control variables for each mental health outcome. To further elucidate variations in relationship between energy use and mental health outcomes by climate regions in urban areas across United States, we applied a stratification analysis by five climate regions based on International Energy Conservation Code and estimated climate zone specific model.

[Figure 1] is about here.

Figure 1 illustrate the relationships between energy burden and the prevalence of frequent mental distress at the census tract level in urban areas across the United States. The key findings are that energy burden is positively related to prevalence of mental distress and that the relationships are also statistically significant in each climate region. For all census tracts, for each additional percentage point increase in the proportion of income spent on energy bills, the prevalence of mental distress increases by 0.473 percentage points at the census tract level, after adjusting for other covariates.

Regarding the relationship between census tract level housing and living characteristics and the prevalence of mental distress, average utility allowance given by the government, percent of crowded housing have a positive relationship with the prevalence of frequent distress. When census tracts have 10 percent point highr in the share of crowded housing and 10 dollar higher in the average utility allowance that houses received from the government compared to other census tracts, the prevalence of frequent mental distress increased by 0.18 and 0.01 by respectively. However, census tracts with old building tended to have lower prevalence of frequent mental distress (See Supplementary table 1).

In terms of census tract level demographic characteristics in relation to the frequent mental distress, a higher percentage of female population, a greater proportion of individuals with less than a high school education, and higher unemployment rates within a census tract are positively correlated with increased prevalence of frequent mental distress. Conversely, a higher percentage of nonwhite population and higher median household income are negatively associated with the prevalence of frequent mental distress.

The findings of the multilevel regression analyses, as presented in Figure 1 and supplementary Tables 2 through 6, reveal a significant positive association between higher energy burden within a census tract and the prevalence of frequent mental distress across five climate regions: very hot, hot and warm, mixed, cool and cold, and very cold regions. Specifically, for each additional percent of household income spent on energy bills, the prevalence of frequent mental distress increases by 0.535, 0.534, 0.481, 0.386, and 0.538 respectively across these regions.

These findings suggest that an increased energy burden within a census tract is consistently associated with a higher prevalence of frequent mental health across all US urban areas and across various climate regions. It implies that as household allocate a larger portion of their income to energy expenses, the mental health of individuals in those census tracts tends to deteriorate that may cause to more frequent experiences of mental distress.

3.3. Census tract level energy burden and diagnosed depression

Shifting focus to the prevalence of depression, as shown in Figure 2, we found that census tract level energy burden is positively associated with the prevalence of physician diagnosed depression in urban areas across the United States and that this relationship are also statistically significant in each climate region. In U.S. urban areas, when households allocate an additional one percent of their income to energy expenses, the prevalence of depression at the census tract level increases by 0.173 percentage points, after accounting for other variables.

[Figure 2] is about here.

Supplementary table 7 provides the multilevel regression result underpinning this relationship. When it comes to census tract level housing and living characteristics, a $10 increase in the average utility allowance provided by the government is associated with a 0.01 percentage point increase in the prevalence of depression. However, the median age of buildings and the percentage of crowded houses within a census tract are negatively associated with depression prevalence. Unlike the positive relationship between building age and frequent mental distress, depression prevalence tends to decrease with older buildings. A one percent increase in crowded housing is associated with a 0.012 percentage point decrease in depression prevalence among adults, consistent with the findings for mental distress.

The relationships between sociodemographic characteristics and the prevalence of adult depression are consistent with those observed for frequent mental distress. A higher percentage of females, a greater proportion of the population with less than a high school education, and higher unemployment rates are positively associated with adult depression. In contrast, a lower share of nonwhite individuals and a higher percentage of older adults are negatively associated with the prevalence of depression among adults. Additionally, median household income is negatively associated with the prevalence of adult depression.

Supplementary Tables through 7 to 12 provides the random intercept regression results stratified by each climate region. controlling for the socio demographic covariates, on average, each additional percentage point of annual energy burden at the census tract is associated with approximately a 0.29 percent increase in the prevalence of depression. In the subgroup analysis stratified by IECC regions, a statistically significant positive association between energy burden and the prevalence of depression is observed in all climate zones with the highest association found in mixed climate zone.

4. Discussion

As the prevalent mental health issues and energy burden phenomena in the United States have recently garnered public concerns in the United States, many previous studies have examined each phenomenon separately. The dearth of such studies leads to questions about the relationship between energy burden and mental health outcomes at a census tract level.

Our study addresses a significant gap in the existing literature by utilizing nationally representative data to examine the relationship between energy burden and mental health outcomes in U.S. urban areas across different climate zones. Using multilevel random intercept models, we found that annual energy burden is a key factor in the prevalence of frequent mental distress and physician-diagnosed depression. Additionally, our study identified that factors such as utility allowance, crowded housing, female population percentage, low education levels, and unemployment have a detrimental impact on the two mental health outcomes, while the percentage of nonwhites, older adults, and median income are negatively associated with these outcomes.

The evidence of the relationship between energy burden and mental health outcomes identified in our study aligns with findings in the existing literature from various regions, including European countries, Canada, Australia, and developing countries such as Ghana and rural China (Bentley et al., 2023; Lin & Okyere, 2020; Oliveras et al., 2021; Riva et al., 2023; Thomson et al., 2017; J. Zhang et al., 2022). Furthermore, our findings emphasize the importance of considering living conditions and physical housing characteristics when examining mental health outcomes. Studies found that building construction materials, living conditions and overall housing quality are critical to indoor thermal comfort, which can significantly influence mental health (Ige et al., 2019; Ormandy & Ezratty, 2012). Living in a cold and damp house and crowded house increase the mental health stressors (Liddell & Guiney, 2015; Mangrio & Zdravkovic, 2018). Old housing is often associated with housing dilapidation, mold and dampness, which can exacerbate residents' well-being and moental health over time.

Our empirical evidence supports that energy justice is interrelated with health justice and that achieving energy justice can be a crucial strategy for addressing health inequalities. As part of the efforts to achieve energy justice in the United States, the US government announced the Federal program titled Justice40 Initiative, directing a significant portion of federal investment to disadvantaged communities that have been disproportionally affected by climate change (Schlosberg & Collins, 2014), energy efficiency (Ghorbany et al., 2024), and infrastructure inequalities (Enviromental Justice, n.d.). Given the complex interplay between energy burden, housing conditions, income levels, and mental health, it is essential to adopt a multifaceted policy approach (Bednar & Reames, 2020; Cong et al., 2023; Graff et al., 2022; Wang et al., 2021) This approach should include a combination of various strategies, such as enhancements to housing conditions (e.g., through weatherization programs (Tonn et al., 2018; Zivin & Novan, 2016)), income-based assistance (e.g., rebates((Datta & Gulati, 2014; Sun & Sankar, 2022)), and measures to alleviate energy burden (e.g., bill assistance (Helmke-Long et al., 2022)). The potential enhancement of mental health resulting from these energy programs emphasizes the need to bolster investments in these initiatives. Additionally, tailoring policy strategies to the specific climate zones and conditions of the affected populations is vital to their effectiveness.

This study has three limitations. First, as the data were aggregated by the census tract, translating the findings from an aggregate level data into the individual or household level would introduce potential for an ecological fallacy. This limitation cannot be easily overcome, as the there is no nationally representative data available that include mental health, energy burden and housing characteristics together at an individual or household level, primary due to concerns about individual privacy. Second, due to limited data availability, some physical housing conditions were solely measured at the county level. Interpreting housing conditions measured at the county level should be approached with caution, as inferring census tract-level outcomes from county-level variables could potentially introduce inaccuracies. In future research, it will be important not only to merge data across the same analytic levels but also to consider housing problems such as leaks, mold, plumbing issues, and lead-based issues that may be associated with health outcomes. These factors should be considered to gain a comprehensive understanding of the relationship between housing conditions and health. Lastly, the causality between energy burden and mental health outcomes cannot be inferred from the data used in our study since they are cross-sectional. However, given that there is a dearth of empirical studies on the topic, our findings provided empirical evidence that energy burden and mental health are strongly associated. In future research, it will be important to answer research questions, such as mechanisms through which energy hardship interplaying with housing conditions and residential energy use affects public health in the US.

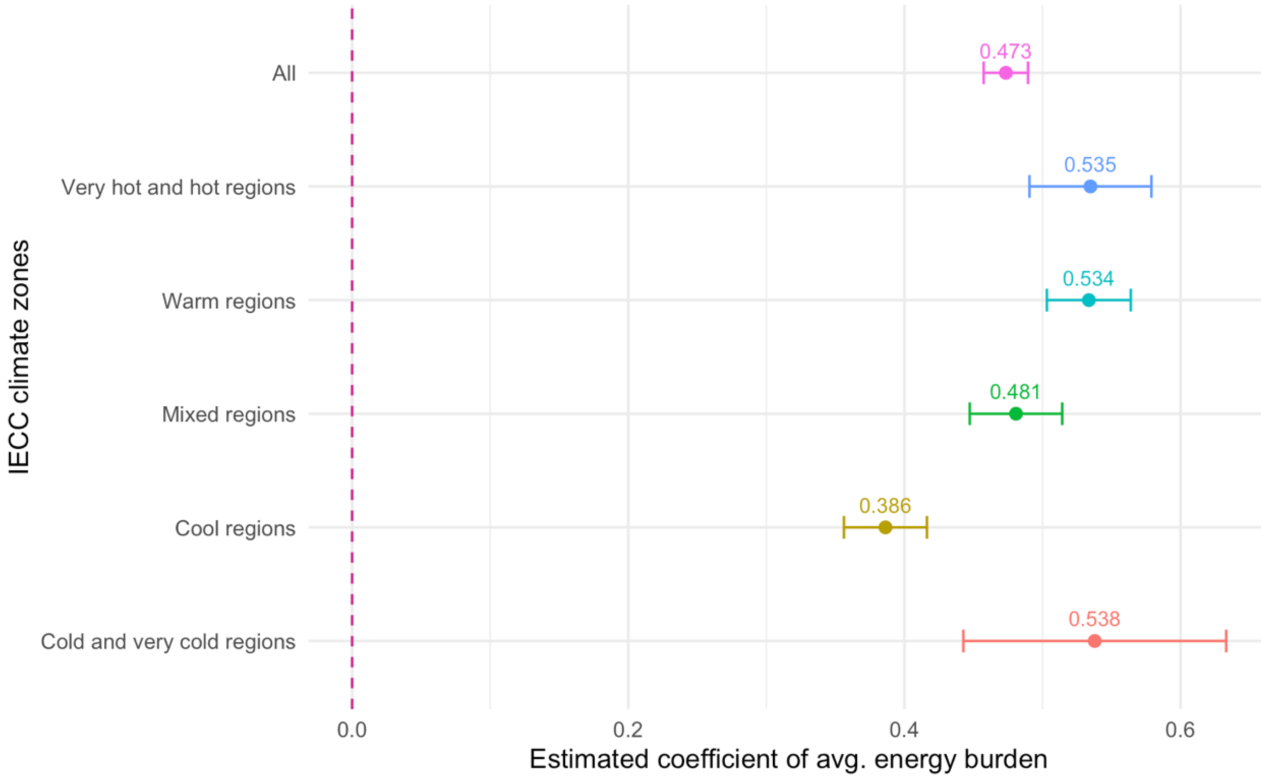
Table 1 Summary of Study Sample

	All		Very Hot and Hot		Warm		Mixed		Cool		Cold and Very Cold	
	M.	*SD*	*M.*	*SD*	*M.*	*SD*	*M.*	*SD*	*M.*	*SD*	*M.*	*SD*
Mental Health Outcomes												
Prevalence of frequent mental distress among adults aged ≥18	13.951	3.587	14.210	3.388	13.500	3.471	13.884	3.454	14.630	3.887	12.897	3.418
Prevalence of physician diagnosed Depression among adults aged ≥18	19.553	3.442	19.273	2.288	18.468	3.311	20.017	4.148	20.490	3.072	21.819	2.837
Energy Burden												
Annual avg. energy burden	3.024	1.834	3.142	1.534	2.545	1.588	3.125	1.615	3.566	2.353	2.717	1.421
Census Tract Level Housing/Living Characteristics												
Avg. utility Allowance (in dollars)	89.114	74.122	91.690	80.614	81.474	75.144	0.075	0.263	97.658	66.651	87.061	55.745
% Crowdedness	5.284	6.660	4.771	5.079	7.615	8.726	5.024	5.896	2.911	3.466	3.181	3.675
Median age of buildings	51.579	19.937	40.485	16.515	46.353	17.385	5.024	5.896	59.008	19.718	58.651	19.935
% Heating fuel type: gas	36.467	27.149	24.154	21.602	58.053	20.736	59.667	22.838	75.442	17.353	73.891	15.112
% Heating fuel type: electricity	57.558	26.230	73.367	21.237	36.961	21.258	29.790	24.605	19.213	15.177	20.178	12.665
% Heating fuel type: others[1)]	4.477	8.239	1.220	1.948	2.232	3.542	9.665	12.378	4.720	8.133	5.135	8.527
County Level Housing Physical/Living Characteristics												
% Wall type = wood frame	71.315	23.653	51.614	21.833	84.089	18.793	67.755	21.609	67.729	22.172	88.869	11.724
% Cooling	99.068	1.607	96.506	1.994	75.645	22.236	85.902	12.334	79.507	8.641	67.537	4.185
% Heating	36.454	16.912	99.356	1.314	98.160	2.251	99.393	0.806	99.749	0.268	99.636	0.353
% Insulated roof	9.092	0.187	31.373	9.117	32.334	10.028	49.199	24.908	33.516	13.522	35.474	9.537
Logged Energy consumption (kwh)	9.092	0.187	9.110	0.087	8.990	0.148	9.008	0.168	9.261	0.125	9.406	0.168
Census Track Level Demographic Characteristics												
% Population: female	51.117	4.368	50.867	4.396	50.823	4.233	51.747	4.476	51.160	4.400	50.665	4.116
% Population: nonwhites	56.139	28.749	59.462	27.592	62.589	25.646	54.890	30.071	48.673	29.468	37.879	27.922

	All		Very Hot and Hot		Warm		Mixed		Cool		Cold and Very Cold	
	M.	*SD*	*M.*	*SD*	*M.*	*SD*	*M.*	*SD*	*M.*	*SD*	*M.*	*SD*
% Population: 65+	13.745	7.086	14.466	9.304	13.280	6.648	14.165	6.467	13.639	6.528	12.757	6.170
% Population: less than high school	15.042	12.260	15.644	13.070	16.915	13.916	13.806	10.348	13.804	10.726	10.880	9.579
% Unemployed	6.607	5.051	6.154	4.121	6.271	4.238	6.380	4.741	7.827	6.649	5.203	4.090
Median HH income (logged)	10.942	0.522	10.871	0.487	11.051	0.518	10.960	0.519	10.832	0.532	10.871	0.448
Climate Zones												
IECC 1 & 2 (Very Hot and Hot)	0.163		-	-	-	-	-	-	-	-	-	-
IECC 3 (Warm)	0.334		-	-	-	-	-	-	-	-	-	-
IECC 4 (Mixed)	0.230		-	-	-	-	-	-	-	-	-	-
IECC 5 (Cool)	0.237		-	-	-	-	-	-	-	-	-	-
IECC 6 & 7 (Cold and Very Cold)	0.035		-	-	-	-	-	-	-	-	-	-
N	25,643		4,191		8,570		5,909		6,068		905	

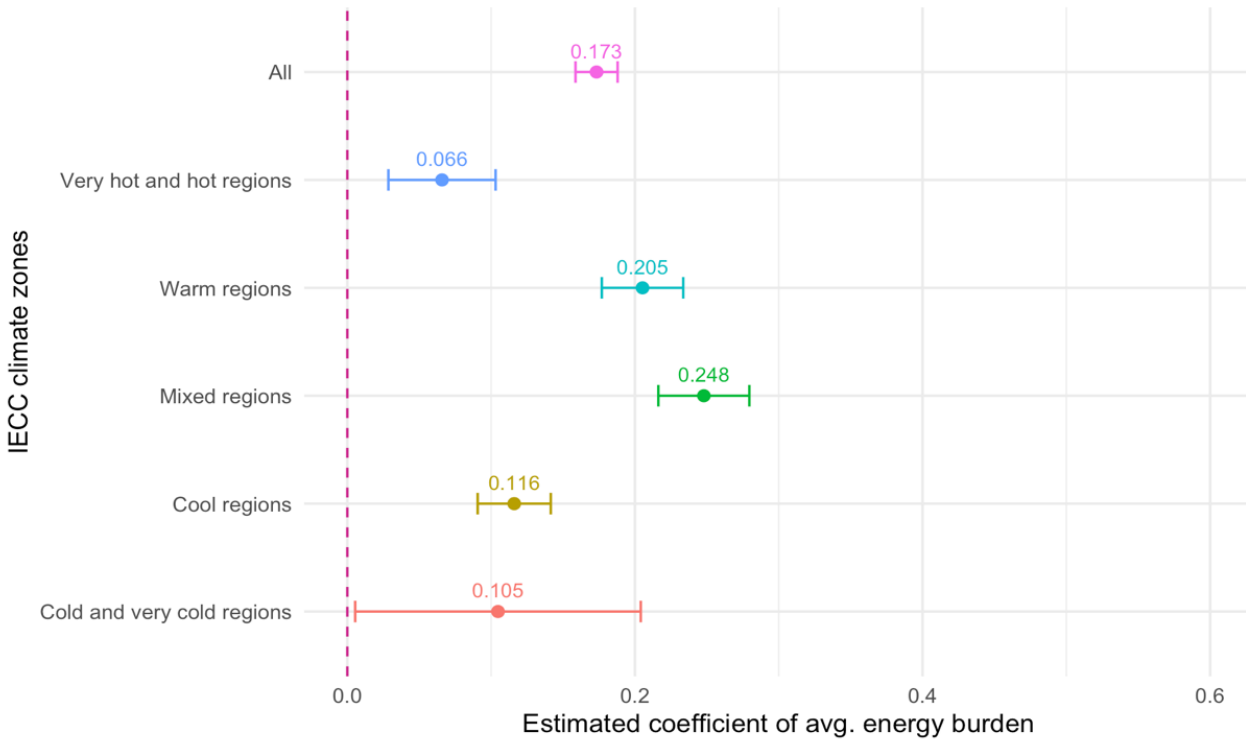
Note: 1) Others include 2) The sample of the study is restricted to 25,643 census tracts spanning in 481 cities across 46 states and the District of Columbia. New Jersey and Alaska and Hawaii were excluded.

Figure 1 Estimated Coefficient of Energy Burden on Prevalence of Frequent Mental Distress by IECC Climate Regions



Note: Points indicates the estimated coefficients and bars represent the 95% C.Is, estimated from random intercept regression models for the total sample and stratified by simplified climate zones. The full model estimations are provided in Supplementary Table 1 to 6.

Figure 2 Estimated Coefficient of Energy Burden on Prevalence of Depression by IECC Climate Regions



Note: Points indicates the estimated coefficients and bars represent the 95% C.ls, estimated from random intercept regression models for the total sample and stratified by simplified climate zones. The full model estimations are provided in Supplementary Table 7 to 12.

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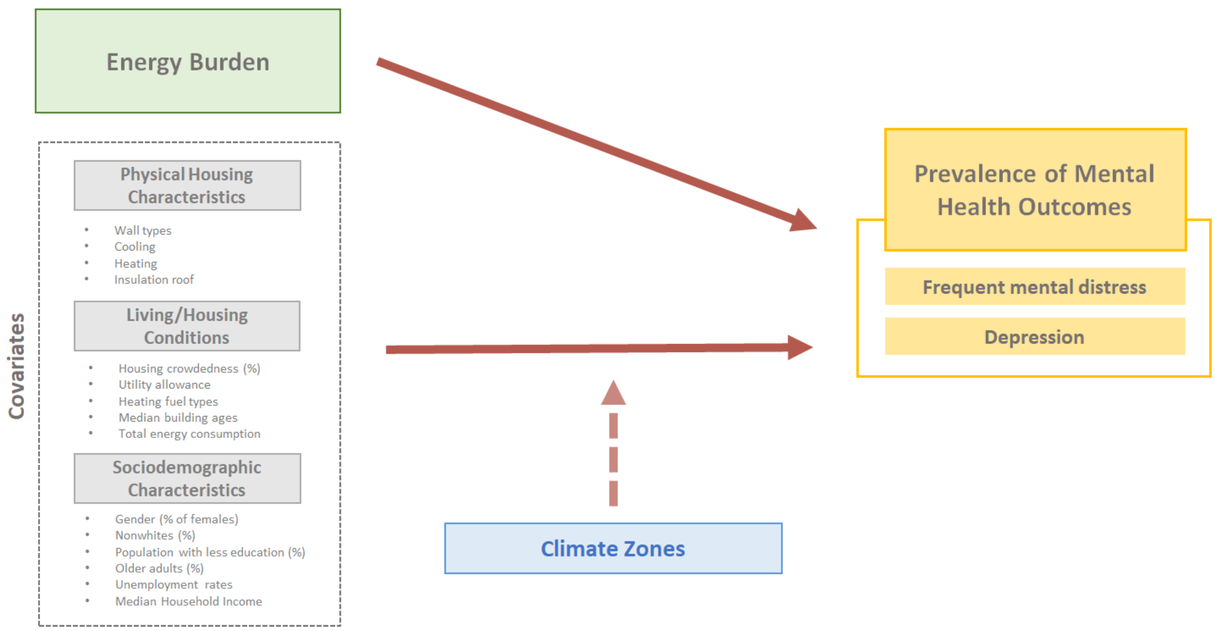
Declaration of interests

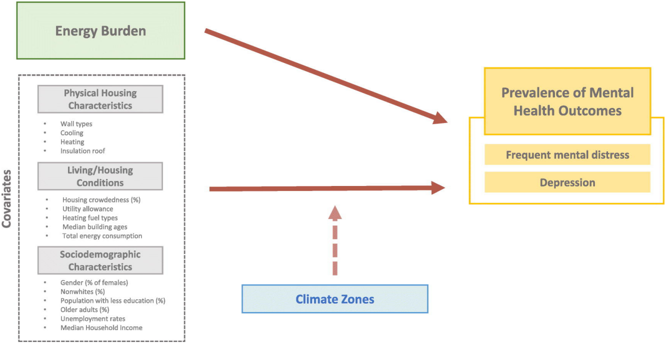
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Graphical abstract

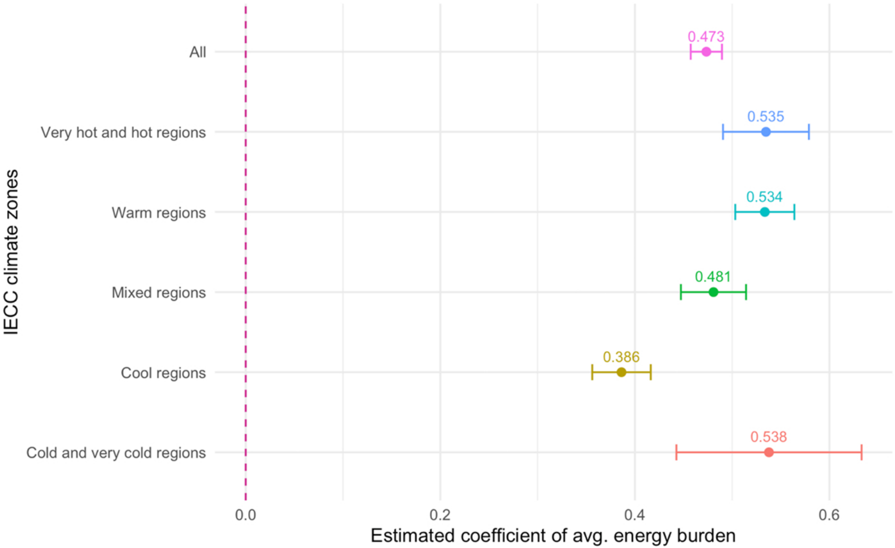


Highlights

- Our study examines energy burden's impact on mental health in U.S. urban areas
- Energy burden positively relates to mental distress and depression prevalence.
- Energy burden's link to mental health is significant across all U.S. climate regions.



Graphics Abstract



IECC climate zones
All
Very hot and hot regions
Warm regions
Mixed regions
Cool regions
Cold and very cold regions
0.473
0.535
0.534
0.481
0.386
0.538
0.0
0.2
0.4
0.6
Estimated coefficient of avg. energy burden

Figure 1

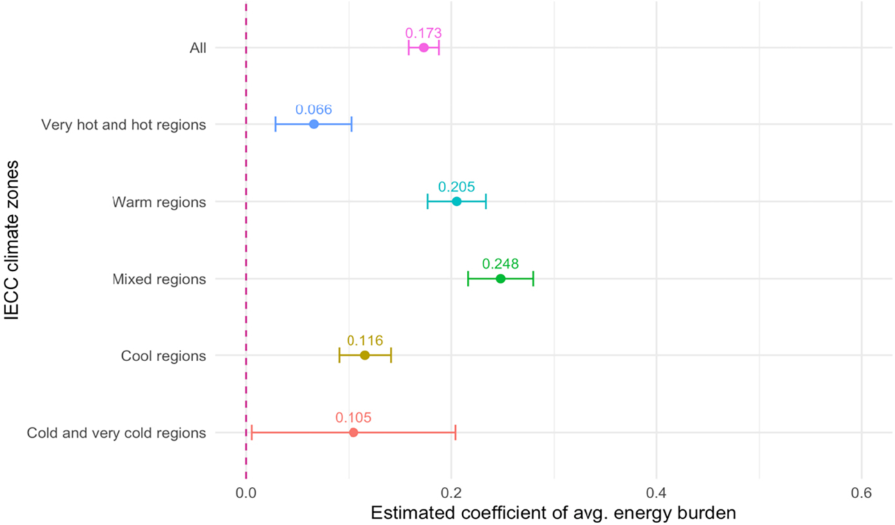

0.173
0.066
0.205
0.248
0.116
0.105
All
Very hot and hot regions
Warm regions
Mixed regions
Cool regions
Cold and very cold regions
IECC climate zones
0.0
0.2
0.4
0.6
Estimated coefficient of avg. energy burden

Figure 2