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Spotlight on energy efficiency in Oregon: Investigating dynamics between energy use and socio-demographic characteristics in spatial modeling of residential energy consumption

Alexandra Buylova

School of Public Policy, Oregon State University, 2251 SW Campus Way, Bexell Hall 100L, Corvallis, 97330, OR, USA

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ABSTRACT

As the state of Oregon transitions to a low-carbon economy, households currently experiencing a high energy cost burden may be vulnerable to future energy price fluctuations. To identify areas susceptible to high energy burden, this study models household energy use intensity on a census-tract level in Oregon. Findings are compared with housing, racial, and sociodemographic characteristics to explore factors associated with high energy use. Finally, energy cost index is constructed and mapped to identify census tracts vulnerable to high energy burden for targeted program and policy development. Study results reveal that census tracts with higher level of energy use intensity have higher percent of older housing, low-income households, households experiencing energy burden, and populations of racial minorities and without high school diploma. This research advances our understanding of differences in energy consumption across diverse population groups and provides detailed information on energy use and energy cost burden for state-level policymaking.

1. Introduction

Housing cost burden is a pressing issue in the United States (Routhier, 2019). Rental affordability has been steadily declining since 2001 (Luque et al., 2019). The Department of Housing and Urban Development (HUD) considers that no more than 30% of household income should go toward housing costs, including rent, mortgage payment, property taxes, utilities, and house insurance (Lin, 2018). In this set of expenditures, utility cost has only recently begun to be recognized as a significant factor in the housing cost burden equation (Kontokosta et al., 2019). Increase in attention could be driven by a potential for growing energy prices as a result of a low-carbon energy transition (Carley et al., 2018), an amplifying number of extreme cold and heat events and an associated increase in energy demands (LIHEAP, 2019), and an attention from the federal level policymakers (Capps, 2019).

A number of studies argue that housing energy efficiency improvements (e.g. changes in a building code, weatherization, energy efficient equipment) could reduce utility costs and improve housing affordability (Wilson et al., 2019; Kontokosta et al., 2019; Drehobl and Ross, 2016; Aroonruengsawat, 2012). Wilson et al. (2019) calculated a potential for $726 savings per year from energy efficiency upgrades for an average household with income below 200% federal poverty level (FPL). Kontokosta et al. (2019) found that energy upgrades in low-income multifamily housing could save up to $1500 in energy costs per year per household. Beyond cost savings, energy efficiency upgrades can improve quality and comfort of the living space, enhancing work productivity and health (Pachuari and Rao, 2014; Chen et al. 2017; Milne and Boardman, 2000; Drehobl and Ross, 2016; Bohr and McCreery, 2019). Finally, energy savings result in reduced greenhouse gas emissions, contributing to global climate targets.

There is a challenge identifying households with high energy cost burden that would benefit the most from energy efficiency work (Walker et al., 2013). A common approach uses a measure of energy burden, which is a percent of household income that is paid for home energy expenses. Energy bill of more than 6–10% of income is considered unaffordable (Hernandez and Bird, 2010; Heindl, 2015; Bird and Hernández, 2012, Drehobl and Ross, 2016; Kontokosta et al., 2019). An unaffordable level of energy costs is predominantly observed among low-income households, attesting to the “income” part as the driver of energy burden. In the analysis of 48 major U.S. cities, Drehobl and Ross (2016) found that an average low-income household energy burden was 7.2%, which is higher than an average higher income household energy burden of 2.3%. Findings from an evaluation of a federal energy assistance program establish that low-income households represent 92% of

E-mail address: buylovaa@oregonstate.edu.

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all households with energy burden of 10% (APPRISE, 2005). Federal Low-Income Home Energy Assistance Program (LIHEAP) designs its funding distribution mechanism based on energy burden levels. Income is used as the main qualifier for this program.

However, low-income households residing in poorly constructed dwellings could be consuming and paying disproportionately more for energy compared to the same income-level family living in a good quality housing. Energy burden is a function of both income and energy consumption. Therefore, to bring more attention to the "energy use" part of energy burden equation and develop a more precise approach in identifying households in need of assistance, this study evaluates household energy consumption and its drivers. More specifically, this study models residential energy use at the census tract spatial resolution for the state of Oregon. In addition, combining energy use data with existing measures of energy burden, housing characteristics and socio-demographic variables, it develops a comprehensive energy cost index to identify areas in the state for targeted energy efficiency interventions. The goal of this research is to assist policymakers and planners in designing programs for reducing energy cost burden and improving energy efficiency in residential housing in Oregon.

2. Data and methods

2.1. Case of Oregon

State of Oregon, located on the West coast of the United States, is home to 3.8 million residents, occupying 1.57 million housing units (2010 U.S. Census). In 2016 residential housing sector represented 23.5% of total state energy consumption, equivalent to 34% of Oregon's greenhouse gas emissions (GHG) emissions that year. Oregon encompasses urban and rural counties, spanning two climate zones. Main residential heating fuel sources are natural gas for homeowners (58%) and electricity for renters (87%). Largest energy end uses in the residential sector include heating and cooling (34%) and water heating (30%) (ODOE, 2018). Oregon has three investor-owned electric utilities and three investor-owned natural gas utilities, regulated by Oregon Public Utility Commission (PUC). A large proportion of the state territory is also served by 36 consumer-owned utilities that encompass electric cooperatives, municipal corporations, and people's utility districts, governed by locally elected boards.

In 2018, approximately 104,000 households with income at or below 50% FPL paid 25% of their income towards utility bills, while households with income between 50% and 100% of FPL – 13% (Fisher et al. 2019). Around 396,182 households (about 25% of state's total) pay more than an affordable level of 6–10% of income towards energy-related expenses (ODOE, 2018). The gap between affordable and actual utility bills equaled to $347 million in 2018 (Fisher et al. 2019). This amount is partially covered by federal energy assistance program LIHEAP, which in 2018 allocated $31.5 million to Oregon. According to 2017 Potential Savings Assessment conducted by the Energy Trust of Oregon, there is a potential to save up to $113 million in energy expenses across low-income households in Oregon from cost-effective energy efficiency upgrades (BEEWG, 2018 p. 5).

Current equity-geared energy efficiency programs that exist in the state include a partnership between the Oregon Department of Housing and Community Services (OHCS), Energy Trust of Oregon (ETO), and other stakeholders and advocate groups that launched a manufactured home replacement pilot that aims to replace aging manufactured homes with code-exceeding energy-efficient new manufactured units. Manufactured homes are typically inhabited by low-income populations. OHCS also administers low-income weatherization programs with funding from federal agencies such as Department of Energy (DOE), Department of Health and Human Services (HHS), and Bonneville Power Administration (BPA), and utility companies. In 2017–2018 fiscal year with total of $41 million weatherization funding, 4785 homes received a service. Weatherization services can include ceiling, wall, and floor insulation; air infiltration reduction; safety repairs; heating equipment repair and replacement; and energy education. Eligible households include families with income below 200% FPL. Finally, a non-profit organization - Energy Trust of Oregon – provides information, cash incentives, and technical assistance to households in the state to help them invest in energy-saving, smart energy solutions, and renewable energy projects. However, ETO receives funding from and therefore serves only customers of Investor Owned Utilities (IOUs) in the state - Portland General Electric, Pacific Power, Northwest Natural, Cascade Natural Gas, and Avista. Moreover, ETO does not have programs that are designed specifically to help low-income or underrepresented customers.

2.2. Data

This research evaluates energy consumption using two datasets: a household energy audit survey – the residential building stock assessment (RBSA) completed by Northwest Energy Efficiency Association (NEEA) in 2017 and the American Community Survey (ACS) 2012–2017 5-year estimates data. RBSA contains detailed information on energy consumption, housing, and household characteristics for a representative sample of 508 occupied primary residences in Oregon. Sampling weights, accounting for the probability of being selected into the sample, are provided and used in the weighted regression analysis (Reames, 2016). This study employs small-area estimation method of combining a regression-based statistical model derived from RBSA with ACS census tract level information. This method has been applied in previous research to identify geographic areas vulnerable to energy poverty and energy insecurity (Fahmy et al., 2011; Walker et al., 2013; Reames, 2016; Min et al., 2010). It is often used to overcome a lack of large samples of household-level energy use data (Min et al., 2010). According to this method, first, energy consumption is modeled for the RBSA dataset to determine the predictors of energy use. Second, derived estimators are applied to a matching set of variables from the ACS dataset to estimate an energy use level for an average household in each 824 census tracts in Oregon.

Regression model of energy use is built as a function of technical building parameters and household characteristics that were found significant in empirical literature (Howard et al., 2012; Min et al., 2010; Reames, 2016; Ewing and Rong, 2008; Adua and Sharp, 2011). In this research, energy use variable is weighted by the area of the living space. This metric, known as an energy use intensity (EUI), is a proxy for household energy efficiency (Howard et al., 2012; Reames, 2016; Wang, 2019). Normalizing energy consumption by a living area of a house provides a more nuanced view on energy performance compared to the total household energy consumption, as smaller units require less energy on average, all other factors being equal (Boardman, 2013).

2.3. Predictors of energy consumption

Prior studies show variation in residential energy consumption across income categories, with low-income households consuming less energy overall compared to non-low-income households (Drehobl and Ross, 2016; Hernández and Bird, 2010; Colton, 2002). This could be driven by the fact that low-income households are more likely to reside in smaller dwellings and have on average less heating floor space (Cluett et al., 2016; Colton, 2002; Kontokosta et al., 2019), while cutting back on energy spending to be able to afford utility bills (Chen et al., 2017; Drehobl and Ross, 2016; EIA, 2015). At the same time, Drehobl and Ross (2016) find that low-income households have higher EUI than other income categories. This could attest to the fact that low-income households tend to live in less energy efficient housing, characterized by air leakages (Chan et al., 2012), inefficient heating and cooling (Drehobl and Ross, 2016), and fewer energy efficient appliances (Xu and Chen, 2019). There is evidence that even government subsidized low-income multifamily housing consumes more energy than its market-rate equivalent properties (Reina and Kontokosta, 2016). Interestingly, Kontokosta et al. (2019) finds a quadratic relationship between EUI and income, with highest and lowest income categories exhibiting highest levels of EUI. For the lowest income category, higher EUI is attributed to density of dwelling occupation and energy inefficiencies, while, for the highest income category, higher EUI is explained by large housing size and greater number of energy-intensive amenities.

Among other household characteristics, which serve as proxies for energy use behavior, age of householders is shown to make a difference in the level of energy consumption. Age is often used as an indicator of the amount of time spent at home and a lifestyle, and therefore a demand for energy consumption (Valenzuela et al., 2014; Fong et al., 2007; Walker and Day, 2012). Differences in energy consumption are also found between owners and renters, with renters having fewer energy efficient appliances and lacking control over energy equipment (Krishnamurthy and Kriström, 2015; Xu and Chen, 2019; Pivo, 2014; Langevin et al., 2013; Davis, 2011). Landlords are often unmotivated to invest in energy efficiency improvements, as they do not directly benefit from reduced utility bills and improved living conditions (Gillingham et al., 2012; Pazuniak et al., 2015). There are also many low-income households among renters (Pivo, 2014). Finally, the number of individuals in a household is associated with higher energy consumption, all else being equal (Gatersleben et al., 2002; Ndiaye and Gabriel, 2011; Valenzuela et al., 2014). However, smaller households consume more energy per person than larger households, possibly because of the shared usage of essential energy devices (Fong et al., 2007).

Other drivers of energy consumption include household size, number of bedrooms, type of housing, type of fuel, and housing age. Larger households have a higher level of energy consumption and EUI than smaller households (Ndiaye and Gabriel, 2011; Valenzuela et al., 2014). Additional bedrooms create added space for heating, cooling, and appliances (Valenzuela et al., 2014). Evidence also suggests that manufactured homes are more inefficient and have higher levels of EUI compared to multifamily and single-family structures (Reames, 2016). Valenzuela et al. (2014) found that houses with natural gas as primary heating fuel were more energy intensive compared to non-gas heating households. Finally, research consistently shows that older homes are less energy efficient compared to newer dwellings due to less stringent building and energy efficiency standards (Wilson et al., 2019; Aroonruengsawat, 2012; Reames, 2016).

Relying on these findings, the final model of energy use intensity is designed as the following:

$$EUI = \beta_0 + \beta_1 \text{Housing Type} + \beta_2 \text{Year of Construction} + \beta_3 \text{Primary Fuel} + \beta_4 \text{Number of Bedrooms} + \beta_5 \text{Income} + \beta_6 \text{Presence of Elderly} + \beta_7 \text{Presence of Children} + \beta_8 \text{Household Size} + \beta_9 \text{Ownership} + \varepsilon$$

2.4. OLS regression model

EUI was calculated by dividing the total annual energy consumption in British Thermal Units (kBTU), as recorded in RBSA, by the conditioned living area of a home (sq. foot). In the regression, EUI dependent variable is expressed as a natural log to correct for heteroskedasticity (Valenzuela et al., 2014; Reames, 2016). After the log transformation, a constant variance between residuals versus fitted plot is observed. Final RBSA sample size had 508 observations, 354 of them had recorded energy use data. During a test for outliers, 11 observations of EUI were dropped. One observation exhibited an extremely low energy use for a relatively large living area. Ten observations, on the other hand, showed an extremely high energy use for a relatively small living area. Observations with negative energy use values were recoded as missing in the process of data cleaning (Walker et al., 2013).

Since the methodological approach required matching two datasets, variables were standardized with respect to their measurements. Each independent variable in the RBSA dataset is represented as a binary variable, while each independent variable from the ACS dataset is standardized as a proportion of households with an associated characteristic in each census tract. Such measurement is comparable to a binary variable in the RBSA (Reames, 2016). Binary variables used in the regression (i.e. 1 = presence of a characteristic, 0 = otherwise), representing housing and household characteristics are the following:

Housing variables:

(1) three binary-coded variables representing type of housing (single family, multifamily, manufactures homes)
(2) four binary-coded variables representing the year of construction (prior to 1960, between 1960 and 1980, between 1980 and 2000, after 2000);
(3) four binary-coded variables representing the primary heating fuel used by a household (electricity, natural gas, fuel oil, wood);
(4) four binary-coded variables representing the number of bedrooms in a unit (no bedrooms, one bedroom, two or three bedrooms, four and more bedrooms).

Household characteristics:

(1) five binary-coded variables representing income categories (under \$20,000, \$20,000-\$50,000, \$50,000-\$80,000, \$80,000-\$150,000, \$150,000 and more);
(2) a binary-coded variable representing ownership (owner = 1, renter = 0);
(3) a binary-coded variable representing a presence of occupants 65 years of age and older;
(4) a binary-coded variable representing a presence of children 10 years of age and younger;
(5) four binary-coded variables representing household size categories (one-person household, two-person household, three-person household, four- and more-person household).

Estimates derived from the regression model are applied to matching housing and household variables from the ACS. After estimating the natural log of EUI for census tracts, values are exponentiated to derive the actual value. This study uses a scaling value of $\exp\left(\frac{RMSE^2}{2}\right)$ during the exponentiation to avoid underestimating the expected values, as suggested by Reames (2016). RMSE is the root mean square error of the model. To estimate final actual values, the following equation is used: $\widehat{E} = \exp\left(\frac{RMSE^2}{2}\right) * \exp.(\widehat{lnE})$.

3. Results

Results of the weighted regression model are displayed in Table 1. Descriptive statistics of dependent and independent variables are available in Table 1 in the Appendix. Final model selection was based on Akaike information criterion (AIC) and Bayesian information criterion (BIC) statistics of model fit. Test of heteroskedasticity (Breusch-Pagan) and multicollinearity (VIF) were conducted as robustness checks. The final model showed slight heteroskedasticity, which was corrected with robust standard errors. Variance inflation factors did not exceed a value of 4.8. The rule of thumb for detecting multicollinearity is VIF being above 5–10 (Menard, 2002). Coefficients displayed in Table 1 were used as indirect estimators for predicting EUI for an average household in each census tract. Parameters with insignificant values were preserved in the final model to avoid the omitted variable bias. Insignificance of the estimators could be a result of correlation between the independent variables, as literature demonstrates.

Table 1
OLS regression model of EUI estimation (RBSA sample).

DV = Log (EUI)	Coefficient	Robust Std. Err.
Housing characteristics		
Single Family	−0.005	0.104
Multi-Family	−0.516***	0.12
Manufactured Home	reference	
Before 1960s	reference	
1960–1980	−0.175**	0.13
1980–2000	−0.095	0.108
After 2000s	−0.332***	0.108
Electricity	−0.240**	0.15
Utility gas	0.025	0.13
Fuel Oil	−0.100	0.19
Wood	reference	
0 bedrooms	0.758*	0.19
1 bedroom	0.535***	0.19
2-3 bedrooms	0.185***	0.10
4 or more bedrooms	reference	
Household characteristics		
Income under $20,000	−0.045	0.19
Income $20,000-$50,000	0.189	0.16
Income $50,000-$75,000	−0.037	0.14
Income $75,000-$150,000	−0.117	0.13
Income above $150,000	reference	
Home ownership	−0.350***	0.10
Presence of elderly	−0.078	0.10
Presence of children	0.125	0.11
Household size 1	−0.400***	0.13
Household size 2	0.027	0.12
Household size 3	−0.015	0.12
Household size 4 and more	reference	
Intercept	4.205***	0.29
N	262	
F-statistic (df = 21; 240)	6.323***	
R-squared	0.356	
Adjusted R-squared	0.300	
AIC	454.8	
BIC	536.9	

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Not included in the final model, but the influence of the state location in two heating and three cooling zones on EUI was tested as a part of the linear regression. No significant impact was found. However, the Kruskal-Wallis test, a non-parametric equivalent of a one-way ANOVA, showed a statistical difference in mean levels of EUI between heating zones as shown in Fig. 1 (Chi-square = 10.9, p-value = 0.001), but not between cooling zones (Chi-square = 4.1, p-value = 0.13). The effect of climate zones in the final regression is likely to be captured by other factors included in the model, resulting in climate zones insignificance. Climate zones variable was not included in the final model, because it lacks an equivalent in the ACS dataset.

Using results from Table 1, average household EUI was predicted for 824 census tracts in Oregon. Ten census tracts were recoded as missing in final ACS sample, because they represent the uninhabited coastal strip territories. In addition, two census tracts within the state territory displayed missing and faulty information and we recoded as missing. Census tract predicted average EUI values range between 34.9 and 64.1 kBTU/sq. foot (Std. dev. = 4.13). According to the Energy Information Administration (EIA), in 2015 average household energy consumption per square foot for the Pacific West region was estimated at 31.5 kBTU (EIA, 2015 RECS). Difference in estimates could be attributed to a variation in measurements and the scale of data aggregation between the datasets. Fig. 2 below displays geographical distribution of EUI across Oregon.

In the RBSA dataset, Kruskal-Wallis and Mann-Whitney *U* test showed no statistical difference between EUI medians for five income groups. However, upon visual evaluation of the data (see Fig. 3), there are a few EUI values for lower income groups that are located toward the higher end of EUI distribution, while EUI values for middle income categories are skewed more towards the lower end of the distribution

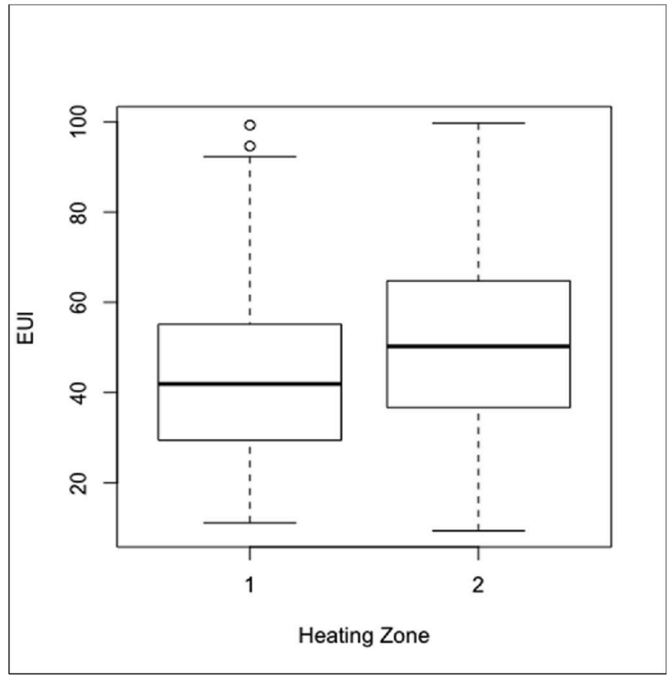

Fig. 1. Mean levels of EUI by heating zones (RBSA dataset).

(see Fig. 3).

However, in the ACS dataset, there is a moderate correlation between predicted average household EUI and income. Higher average EUI is associated with higher percent of households with income between $20,000-$50,000 (r = 0.19, p = 0.00) and lower percent of households with incomes between $75,000-$150,000 and above $150,000 (r = −0.12, p = 0.0 and r = −0.12, p = 0.0, respectively). Higher EUI is also associated with higher percent of population with income below 200% FPL and lower average annual income (see Table 2). The relationship between EUI and income is important, because these two factors are the components of energy burden. Significant correlation between EUI and income confirms results of previous studies that argue that lower income households tend to consume more energy when normalized by living area, compared to higher income households.

In addition, Table 2 demonstrates statistically significant relationships between predicted EUI and other socio-demographic, racial, and housing characteristics. Higher average EUI is associated with higher percent of houses constructed before 1960 (r = 0.66); lower median year of housing construction (r = −0.62); higher percent of energy burdened households (r = 0.17); higher percent of non-white energy burdened households with income below 60% Area Median Income (AMI) (r = 0.21); higher average energy burden of households with incomes below 60% AMI; higher percent Hispanic population (r = 0.12); higher percent population over 25 years of age without high school diploma (r = 0.22); higher percent population with incomes below 200% FPL (r = 0.20); and lower median household income (r = −0.16). The strongest relationship is between EUI and the year of housing construction. This result confirms that older houses tend to be less energy efficient. Descriptive statistics of variables in Table 2 are provided in the Appendix.

These is a growing demand to investigate housing and energy cost burdens among racial groups to design more effective and equitable housing policy (Kontokosta et al., 2019). Energy justice community calls for an evaluation of structural attributes and social values embedded in housing and energy policies (Goldthau and Sovacool, 2012; Jenkins et al., 2018). Responding to the demand, a number of studies find higher energy cost burden among racial minority groups (Reames, 2016; Drehobl and Ross, 2016; Bednar et al., 2017; Kontokosta et al., 2019). Similarly, this study also determined a positive association between

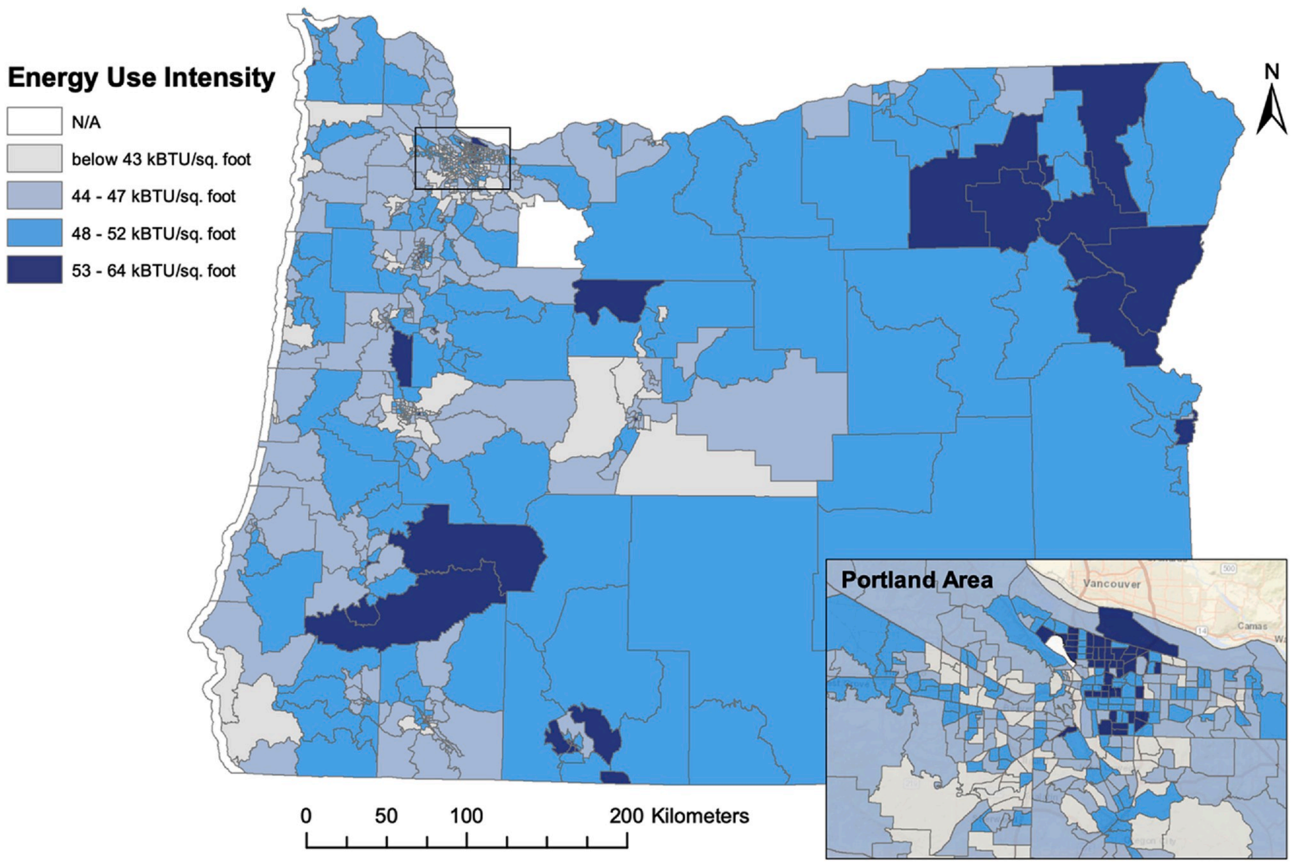

Fig. 2. Geographical distribution of average household EUI by census tract in Oregon (colors are important to convey the meaning). Census tract legal boundaries are derived from Census TIGER/Line Shapefiles, 2012.

average household EUI, percent non-white energy burdened households, and percent Hispanic population. However, the correlation value is not large. It is important to note, that Oregon population is less diverse compared to the U.S. as a whole. Household racial composition of Oregon consists of 88.6% White households, 2.7% Black households, 3.1% Native American households, 5.2% Asian households, and 11.7% Hispanic households. Therefore, it is less likely to observe strong statistical differences in EUI distribution across racial groups. However, as Table 2 demonstrates, there is evidence suggesting differences in EUI levels across racial minority groups. Moreover, there are pockets of high concentration of racial and ethnic minority groups throughout Oregon, e.g. Black neighborhoods in Eastern Portland, Hispanic population in Marion county, and nine federally recognized Oregon tribes. As Fig. 2 shows, highest levels of EUI are noted, among other census tracts, for Eastern Portland and Warm Springs Indian Reservation territory.

3.1. Comprehensive energy cost index

Based on the above results, this study developed a comprehensive index to identify census tracts vulnerable to higher energy cost burden. The index is used to locate census tracts in need for energy efficiency interventions. The index is composed of four elements that speak to energy cost burden, even though they do not represent its direct measurement per se. Parameters correspond to energy use, poverty, housing quality, and racial justice. Similar scores have been developed by Reames (2016) and Walker et al. (2013). The need for a comprehensive index and a targeted approach is explained by the multi-dimensionality of the energy cost problem, limited resources for addressing the problem, and the necessity of considering other elements beyond income in identifying vulnerable populations. More specifically, energy cost index includes the following variables: average household EUI, median household income, median year of housing construction, and percent non-white energy burdened households with income below 60% AMI. Census tracts with higher than the study area mean EUI (46.8 kBTU/sq. foot), higher than the area mean percent non-white energy burdened households (2.3%), lower than the study area mean median household income ($59,515), and lower than the area mean median year of housing construction (1977) are placed into the energy risk group. Two versions of the energy cost index are developed. One index includes all four parameters. The second index excludes percent non-white energy burdened households. Spatial location of energy risk census tracts identified according to these indexes is displayed in Figs. 4 and 5.

Because of the fewer criteria used to calculate the energy cost index displayed Fig. 4 compared to Fig. 5, more census tracts qualify as vulnerable areas to high energy cost in Fig. 4. Eastern, North-Eastern, and South-Western regions of Oregon, as well as Eastern and North-Eastern neighborhoods of Portland, display higher concentrations of census tract vulnerable to high energy cost (see Fig. 4). When racial minority variable is added into the energy cost index (Fig. 5), Eastern and North-Eastern parts of the state still display the presence of census tracts vulnerable to high energy costs, suggesting higher concentrations of racial minorities subjected to energy burden in these areas. Census tracts vulnerable to high energy cost in Portland area did not change significantly with an addition of a racial minority variable in to the energy cost index (see Fig. 5), implying that census tracts with higher percent of racial minority households experiencing energy burden are also the census tracts with higher levels of mean EUI, lower median income, and older housing stock in those areas of Portland.

4. Conclusion and policy implications

This study predicted average household energy consumption for

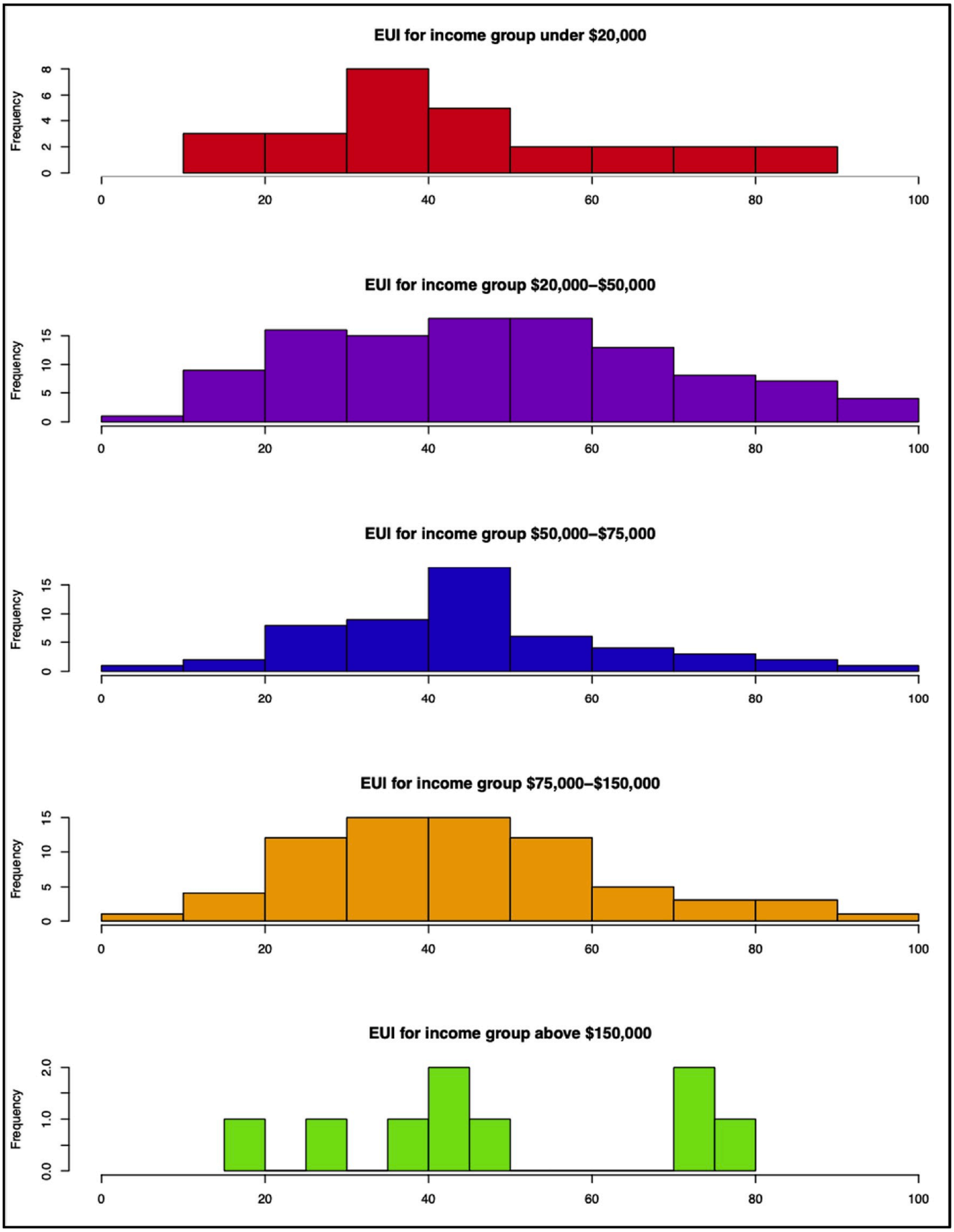

Fig. 3. EUI distribution by income groups in the RBSA dataset.

each census tract in Oregon via Energy Use Intensity (EUI). Results demonstrate differences in spatial distribution of EUI across the state and by sociodemographic and housing characteristics. Census tracts with higher levels of energy use intensity exhibit higher percent of energy burdened, low-income, and households without a high school diploma. In addition, census tracts with higher average household EUI also demonstrate higher percent of homes built prior to 1960. This result supports an assumption that older homes are less likely to conform to rigorous energy efficiency standards. Moreover, similar to prior research, this study findings signal that low-income and racial and ethnic minority groups are more likely to live in older and less energy efficient housing (Adua and Sharp, 2011; Lutzenhiser and Gossard, 2000; Lewis et al., 2019). This result could aid the state of Oregon and executive agencies in their efforts in regard to racial justice and providing equitable affordable housing to their citizens. This study shows that race and ethnicity are factors that contribute to the differences in household energy use. Therefore, this research also further advances energy studies scholarship that investigates differences in energy use across racial and ethnic groups.

This study also identified energy risk census tracts based on average

Table 2
Pearson's correlation between demographics, socioeconomics, and predicted EUI in the ACS.

Category	Description	Pearson's correlation
Housing age	Percent houses constructed before 1960	0.66***
	Median year of housing construction	−0.63***
Energy burden	Percent energy burdened households	0.17***
	Percent non-white energy burdened households <60% AMI	0.21***
	Average energy burden of households <60%AMI	0.17***
Ethnicity	Percent Hispanic population	0.12***
Education	Percent population over 25 without HS diploma	0.22***
Income	Percent population <200%FPL	0.20***
	Median household income	−0.10***

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

household levels of EUI, percent non-white energy burdened households, median household income, and median year of housing construction. The goal of identifying and locating such census tracts was to provide detailed information on energy cost burden, including measures beyond energy use and income, for state-level program and policy development to reduce household energy costs. As research shows, energy consumption is a multifaceted issue, embedded with structural components and values. Final results are presented via a map. Visual representation of information aids in the process of data interpretation and allows to identify spatial dependencies. Policymakers and planners can use maps produced in this research to begin and guide their conversations around energy use and its drivers in the state to design more effective and equitable policies. As a part of ongoing efforts by state agencies and advocates in the state of Oregon, during the 2020 State Legislative Session HB4067 A was introduced, aiming to authorize Public Utility Commission to consider differential energy burden and other inequities of affordability and environmental justice in setting utility rates of PUC customers. The bill was not passed in 2020. However, it gained attention and traction, with chances on being passed into law in the subsequent years. Results of this research could aid groups working to advance this legislative measure (Oregon Legislative Assembly, 2020). Numerous non-profit groups that advocate for low-income and underrepresented communities in the state support these legislative efforts. These groups include the Renewable Energy Coalition, Renewable Northwest, Oregon Environmental Council, Verde, Northwest Energy Coalition, Climate Solutions, and others. Finally, this research highlighted that, for some households, energy spending can be financially burdensome. Therefore, this study encourages policymakers to consider energy use and its drivers when designing policies that address the issue of housing affordability.

Computation of EUI for the state of Oregon was done with purpose of helping the state to address issues of energy burden and poor-quality housing stock. The study contends that in addition to "income" driver of energy cost burden, it is valuable to consider other factors, such as energy use, housing, and social value parameters, in developing more precise and socially acceptable policies. This work argues that in the process of setting goals to reduce energy cost burden, policymakers need to take into an account the level of household energy use, age of a housing stock, and racial composition of the population. Geographic map of energy risk groups distribution identifies areas most vulnerable to energy cost burden. These are the census tracts that require attention today and in the future as the state puts forward policies affecting energy resource base.

Partially, this study was motivated by a lack of large sample of household energy use data for the state of Oregon. Comprehensive energy data allows to track energy consumption over time, measure effectiveness of any program interventions, and design better policies to achieve set energy targets. The difficulty of getting access to detailed household energy use information still exists. To make such data

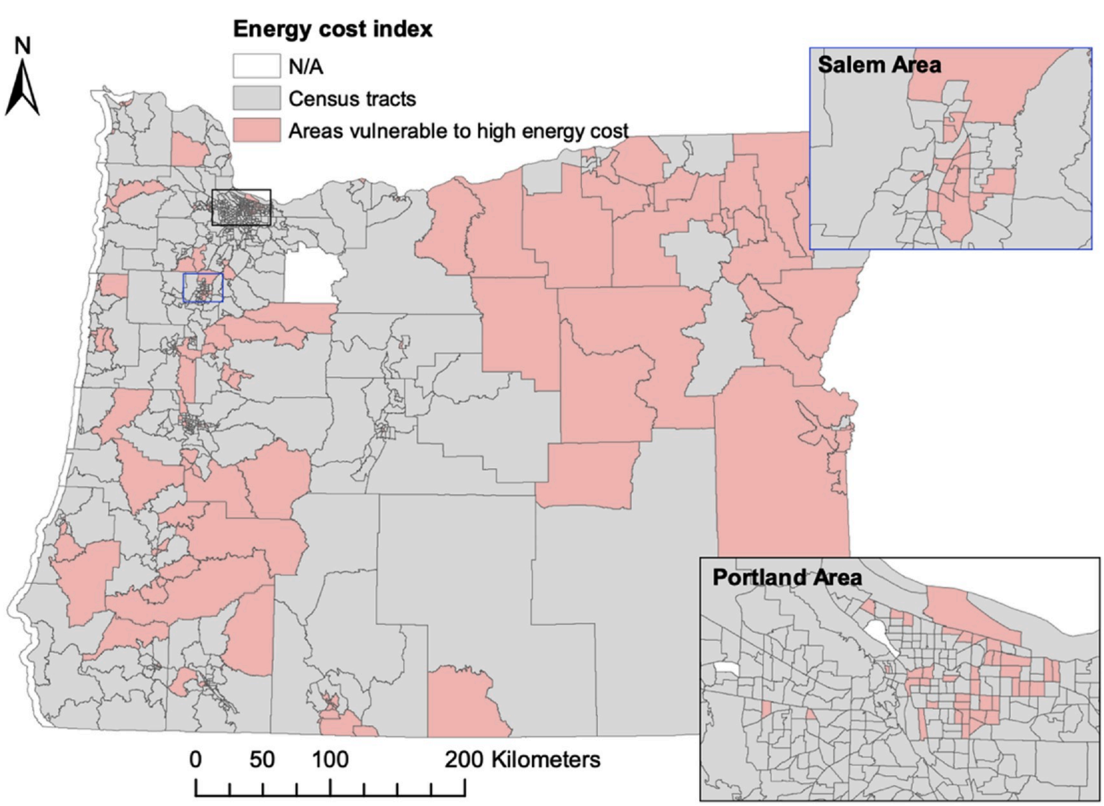

Fig. 4. Geographic distribution of energy risk groups *without* racial minority variable (Index includes measures of mean EUI, median income, and media housing age).

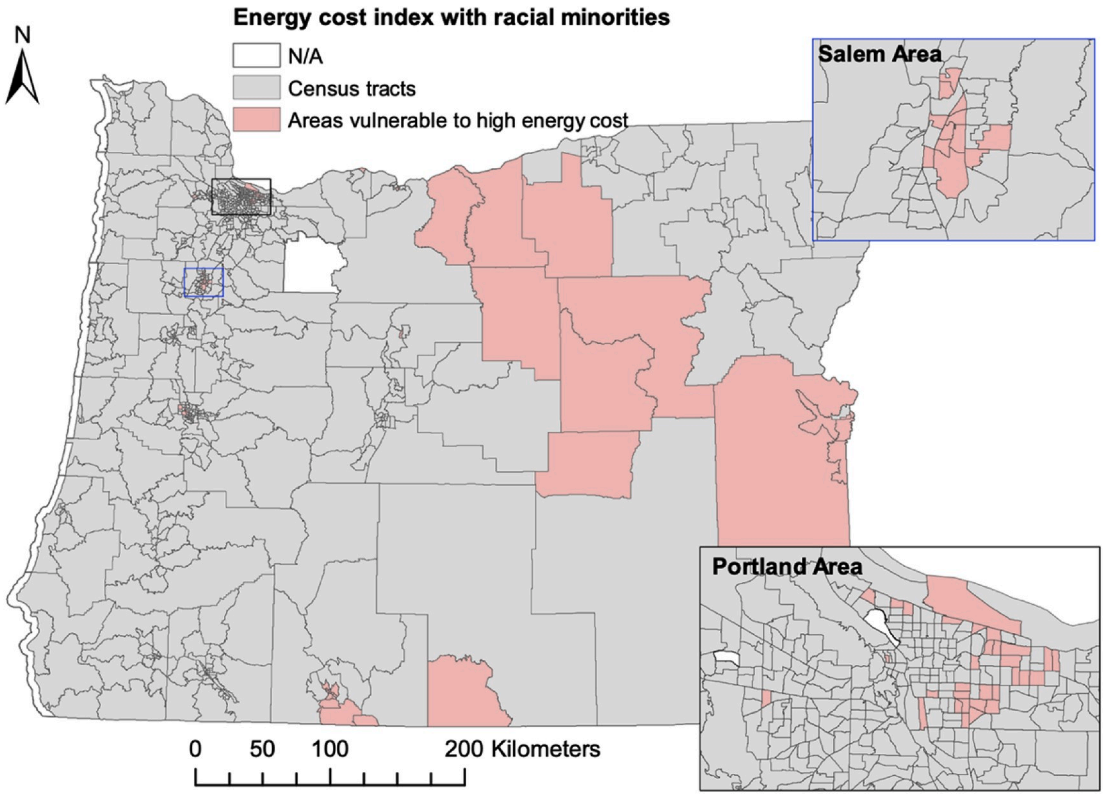

Fig. 5. Geographic distribution of energy risk groups *with* racial minority variable (Index includes measures of EUI, median income, median housing age, and percentage non-white energy burdened households below 60% AMI).

available for research and evaluation, policymakers can consider adopting energy disclosure policies. A recent report by American Council for an Energy-Efficient Economy provides a guide to establishing residential sector energy disclosure requirements (ACEEE, 2019).

This study evaluated household energy use as a component of energy burden equation. Together with income, they constitute the two main drivers of residential housing energy cost. However, this study did not consider the role of efficiency of different fuel types and their distribution across the state and energy price and its impact on the variation of energy cost distribution. The future research should continue improving estimations of energy use intensity and energy burden by considering contributions of energy use by fuel type, energy prices, and utility cost schemes to energy cost burden. The role of energy price may be especially important in the future as utility portfolios shift towards greater percentage of cleaner and renewable energy sources, carrying cost implications for energy consumers. Future research may also consider looking at temporal variation in energy cost burden and its association with changing energy prices, because they tend to fluctuate more over time compared to income or energy use behavior.

This study calculated a census-tract level average energy use intensity for the state of Oregon and analyzed its association with housing age, household characteristics of income, race, energy burden, and education. It also developed an energy cost index that was used to identify geographic areas in the state that are the most vulnerable to high energy cost burden. This research advances our understanding of differences in energy consumption across different population groups and provides detailed information on energy use and energy cost burden for state-level policymaking. This work is timely, as the state of Oregon gradually transitions to a low-carbon economy. The process carries potential benefits but can also result in a disproportionate negative impact on certain parts of the state. This study helps identify those areas to develop and implement preventative measures and reduce current energy cost burden via energy efficiency program interventions.

Data availability

Datasets used in this article and the R-code created for the analysis are available at Zenodo open access repository under Creative Commons license:10.5281/zenodo.3703524.

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Declaration of competing interest

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CRediT authorship contribution statement

Alexandra Buylova: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing.

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Appendix

Table 1
Variable Description. Residential Building Stock Assessment. Unit of analysis: household.

Variable (variable name in the dataset)	Description	Descriptive Statistics
Annual Energy Use	Total annual energy use for each housing unit in the dataset was calculated by summing up energy use for each type of fuel as recorded in the database. Observations with negative and values of 0 were recorded as missing. Unit of measurement is kBTU (British Thermal Units in thousands).	N = 354 Mean = 75, 633 Std. dev. = 45, 730 Min = 4500 Max = 532, 587
Conditioned floor area	Conditioned floor area was calculated in the survey using exterior perimeter measurements where practical and interior measurement are necessary. Conditioned areas include: Living space; Closets, including invented mechanical closets; Basements, unless the basement is clearly outside of the thermal and pressure boundary of the home; Encapsulated crawlspaces, which are rare in the Northwest; Attic spaces that have been sealed and insulated at their exterior surfaces, which are rare in the Northwest. This measurement is located in Site One Line file of the RBSA database. Unit of measurement is square feet.	N = 379 Mean = 1780 Min = 270 Max = 7, 500
Energy Use Intensity (*eui*)	EUI was calculated by dividing annual energy use by conditioned floor area. Unit of measurement is kBTU/sq. foot.	N = 348 Mean = 46.3 Std. dev. = 20 Min = 9.37 Max = 99.7
Single family (*SF*)	Binary variable (1 = yes, 0 = no)	N = 508 Mean = 0.48 Std. dev. = 0.5
Multifamily (*MF*)	Binary variable (1 = yes, 0 = no)	N = 508 Mean = 0.31 Std. dev. = 0.46
Manufactured home (*MH*)	Binary variable (1 = yes, 0 = no)	N = 508 Mean = 0.2 Std. dev. = 0.4
Site built before 1960 (*pre1960ACS*)	Binary variable (1 = yes, 0 = no)	N = 478 Mean = 0.2 Std. dev. = 0.4
Site built between 1960 and 1980 (*yr1960ACS*)	Binary variable (1 = yes, 0 = no)	N = 478 Mean = 0.27 Std. dev. = 0.44
Site built between 1980 and 2000 (*yr1980ACS*)	Binary variable (1 = yes, 0 = no)	N = 478 Mean = 0.35 Std. dev. = 0.48
Site built after 2000 (*yr2000ACS*)	Binary variable (1 = yes, 0 = no)	N = 478 Mean = 0.19 Std. dev. = 0.39
Electricity as a primary fuel (*Electricity_dummy*)	Binary variable (1 = yes, 0 = no)	N = 354 Mean = 0.55 Std. dev. = 0.5
Natural gas as a primary fuel (*Gas_dummy*)	Binary variable (1 = yes, 0 = no)	N = 354 Mean = 0.35 Std. dev. = 0.48
Fuel oil as a primary fuel (*Fuel_oil_dummy*)	Binary variable (1 = yes, 0 = no)	N = 354 Mean = 0.01 Std. dev. = 0.11
Wood as a primary fuel (*Wood_dummy*)	Binary variable (1 = yes, 0 = no)	N = 354 Mean = 0.1 Std. dev. = 0.28
Income category under $20,000 (*Income1*)	Binary variable (1 = yes, 0 = no)	N = 378 Mean = 0.18 Std. dev. = 0.39
Income category $20,000-$50,000 (*Income2*)	Binary variable (1 = yes, 0 = no)	N = 378 Mean = 0.41 Std. dev. = 0.49
Income category $50,000-$80,000 (*Income3*)	Binary variable (1 = yes, 0 = no)	N = 378 Mean = 0.17 Std. dev. = 0.38
Income category $80,000-$150,000 (*Income4*)	Binary variable (1 = yes, 0 = no)	N = 378 Mean = 0.21 Std. dev. = 0.41
Income category $150,000 and more (*Income5*)	Binary variable (1 = yes, 0 = no)	N = 378 Mean = 0.03 Std. dev. = 0.18
Ownership (*Ownership*)	Binary variable (1 = owner, 0 = renter). In the original database owners and owners in the process of buying or with mortgage are recorded as owners.	N = 493 Mean = 0.69 Std. dev. = 0.46
Number of bedrooms - 0 (*bed0*)	Binary variable (1 = yes, 0 = no)	

(*continued on next page*)

Table 1 (*continued*)

Variable (variable name in the dataset)	Description	Descriptive Statistics
		N = 501 Mean = 0.006 Std. dev. = 0.08
Number of bedrooms - 1 (*bed1*)	Binary variable (1 = yes, 0 = no)	N = 501 Mean = 0.15 Std. dev. = 0.36
Number of bedrooms – 2–3 (*bed2_3*)	Binary variable (1 = yes, 0 = no)	N = 501 Mean = 0.71 Std. dev. = 0.45
Number of bedrooms – 4 and more (*bed4_more*)	Binary variable (1 = yes, 0 = no)	N = 501 Mean = 0.13 Std. dev. = 0.34
Presence of elderly above 65 years of age (*Older present*)	Binary variable (1 = yes, 0 = no)	N = 497 Mean = 0.41 Std. dev. = 0.49
Presence of children below 10 years of age (*Presence of children*)	Binary variable (1 = yes, 0 = no)	N = 496 Mean = 0.17 Std. dev. = 0.38
Household size – 1 occupant (*hh1_dummy*)	Binary variable (1 = yes, 0 = no)	N = 501 Mean = 0.26 Std. dev. = 0.44
Household size – 2 occupants (*hh2_dummy*)	Binary variable (1 = yes, 0 = no)	N = 501 Mean = 0.43 Std. dev. = 0.5
Household size – 3 occupants (*hh3_dummy*)	Binary variable (1 = yes, 0 = no)	N = 501 Mean = 0.15 Std. dev. = 0.36
Household size – 4 and more occupants (*hh4_dummy*)	Binary variable (1 = yes, 0 = no)	N = 501 Mean = 0.15 Std. dev. = 036

Table 2
Variable Description. American Community Survey (ACS, 2012–2017 5-year estimates). Unit of analysis: Census tract.

Variable	Description	Descriptive statistics
Single family (*SF*)	Proportion of occupied housing units within a census tract ACS table #S2504	N = 825 Mean = 0.69 Std. dev. = 0.18 Min = 0.008 Max = 1
Multifamily (*MF*)	Proportion of occupied housing units within a census tract ACS table #S2504	N = 825 Mean = 0.22 Std. dev. = 0.2 Min = 0.0 Max = 0.98
Manufactured home (*MH*)	Proportion of occupied housing units within a census tract ACS table #S2504	N = 825 Mean = 0.087 Std. dev. = 0.1 Min = 0.0 Max = 0.67
Site built before 1960 (*pre1960ACS*)	Proportion of occupied housing units within a census tract ACS table #S2504	N = 825 Mean = 0.27 Std. dev. = 0.22 Min = 0.0 Max = 0.96
Site built between 1960 and 1980 (*yr1960ACS*)	Proportion of occupied housing units within a census tract ACS table #S2504	N = 825 Mean = 0.3 Std. dev. = 0.14 Min = 0.009 Max = 1
Site built between 1980 and 2000 (*yr1980ACS*)	Proportion of occupied housing units within a census tract ACS table #S2504	N = 825 Mean = 0.27 Std. dev. = 0.14 Min = 0.0 Max = 0.8
Site built after 2000 (*yr2000ACS*)	Proportion of occupied housing units within a census tract ACS table #S2504	N = 825 Mean = 0.16 Std. dev. = 0.12 Min = 0.0 Max = 0.77
Electricity as a primary fuel (*Electricity*)	Proportion of occupied housing units within a census tract ACS table #S2504	N = 825 Mean = 0.5

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Table 2 (*continued*)

Variable	Description	Descriptive statistics
		Std. dev. = 0.19 Min = 0.07 Max = 1
Natural gas as a primary fuel (*Gas*)	Proportion of occupied housing units within a census tract ACS table #S2504	N = 825 Mean = 0.37 Std. dev. = 0.23 Min = 0.0 Max = 0.9
Fuel oil as a primary fuel (*Fuel_oil*)	Proportion of occupied housing units within a census tract ACS table #S2504	N = 825 Mean = 0.025 Std. dev. = 0.036 Min = 0.0 Max = 0.32
Income category under $20,000 (*Income1*)	Proportion of occupied housing units within a census tract ACS table #B19001	N = 824 Mean = 0.16 Std. dev. = 0.088 Min = 0.008 Max = 0.68
Income category $20,000-$50,000 (*Income2*)	Proportion of occupied housing units within a census tract ACS table #B19001	N = 825 Mean = 0.29 Std. dev. = 0.088 Min = 0.0 Max = 0.55
Income category $50,000-$80,000 (*Income3*)	Proportion of occupied housing units within a census tract ACS table #B19001	N = 825 Mean = 0.18 Std. dev. = 0.048 Min = 0.039 Max = 0.34
Income category $80,000-$150,000 (*Income4*)	Proportion of occupied housing units within a census tract ACS table #B19001	N = 825 Mean = 0.27 Std. dev. = 0.09 Min = 0.013 Max = 0.77
Income category $150,000 and more (*Income5*)	Proportion of occupied housing units within a census tract ACS table #B19001	N = 825 Mean = 0.099 Std. dev. = 0.093 Min = 0.0 Max = 0.58
Ownership (*Ownership*)	Proportion of occupied housing units within a census tract ACS table #S2504	N = 825 Mean = 0.63 Std. dev. = 0.19 Min = 0.005 Max = 0.97
Number of bedrooms - 0 (*bed0*)	Proportion of occupied housing units within a census tract ACS table #S2504	N = 825 Mean = 0.026 Std. dev. = 0.05 Min = 0.0 Max = 0.57
Number of bedrooms - 1 (*bed1*)	Proportion of occupied housing units within a census tract ACS table #S2504	N = 825 Mean = 0.095 Std. dev. = 0.08 Min = 0.0 Max = 0.53
Number of bedrooms – 2–3 (*bed2_3*)	Proportion of occupied housing units within a census tract ACS table #S2504	N = 825 Mean = 0.7 Std. dev. = 0.12 Min = 0.12 Max = 0.93
Number of bedrooms – 4 and more (*bed4_more*)	Proportion of occupied housing units within a census tract ACS table #S2504	N = 825 Mean = 0.18 Std. dev. = 0.11 Min = 0.0 Max = 0.66
Presence of elderly above 65 years of age (*Elderly*)	Proportion of occupied housing units within a census tract ACS table #DP05	N = 825 Mean = 0.42 Std. dev. = 0.16 Min = 0.0 Max = 1
Presence of children below 10 years of age (*Children*)	Proportion of occupied housing units within a census tract ACS table #DP05	N = 825 Mean = 0.3

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Table 2 (*continued*)

Variable	Description	Descriptive statistics
		Std. dev. = 0.12 Min = 0 Max = 0.84
Household size – 1 occupant (*hh1_dummy*)	Proportion of occupied housing units within a census tract ACS table #S2501	N = 825 Mean = 0.28 Std. dev. = 0.098 Min = 0.04 Max = 0.81
Household size – 2 occupants (*hh2_dummy*)	Proportion of occupied housing units within a census tract ACS table #S2501	N = 825 Mean = 0.37 Std. dev. = 0.074 Min = 0.18 Max = 0.66
Household size – 3 occupants (*hh3_dummy*)	Proportion of occupied housing units within a census tract ACS table #S2501	N = 825 Mean = 0.15 Std. dev. = 0.044 Min = 0 Max = 0.3
Household size – 4 and more occupants (*hh4_dummy*)	Proportion of occupied housing units within a census tract ACS table #S2501	N = 825 Mean = 0.21 Std. dev. = 0.078 Min = 0 Max = 0.45
Median year of housing construction (*median house year*)	Data is retrieved from ACS table #B25035	N = 824 Mean = 1974 Std. dev. = 14.9 Min = 1939 Max = 2004
Median household income (*median income*)	Data is retrieved from ACS table #B19013	N = 825 Mean = 59,514 Std. dev. = 22,473 Min = 10,753 Max = 177,672
Percent energy burdened households (*percent energy burdened*)	Variable is calculated using ACS 2012–2017 microdata. First, energy burden was calculated for each household in the microdata dataset. Households with energy burden above 6% were flagged as energy burdened. Observations were aggregated for PUMA (Public Use Microdata Area) statistical areas to identify percent of energy burdened households in each PUMA. Then, PUMA to census tract conversion using weights from Missouri Geographic Correspondence Engine was applied to identify percent energy burdened households for census tracts (http://mcdc1.missouri.edu/applications/geocorr2014.html)	N = 825 Mean = 20.3 Std. dev. = 6.6 Min = 10.4 Max = 34.6
Proportion non-white energy burdened households below 60% AMI (*percent_nonwhiteEB*)	Variable is calculated using ACS 2012–2017 microdata. Non-White households are identified by the race of the household head. Variable is recorded as a proportion.	N = 825 Mean = 0.023 Std. dev. = 0.014 Min = 0.008 Max = 0.083 (8.3%)
Average energy burden for households below 60% AMI (*AverageEB60AMI*)	Variable is calculated using ACS 2012–2017 microdata. Area median income is calculated for PUMA area. Variable is recorded in percentages.	N = 825 Mean = 8.9 Std. dev. = 1.4 Min = 5.7 Max = 11.3
Percent Hispanic population (*pop_percent_hispanic*)	Data is retrieved from ACS table #DP05	N = 825 Mean = 11.8 Std. dev. = 10.8 Min = 0 Max = 74.5
Percent population below 200% FPL (*percent_pop200FPL*)	Data is retrieved from ACS table #S1701	N = 825 Mean = 34.3 Std. dev. = 14.5 Min = 5.5 Max = 90.9
Percent population over 25 without HS diploma (*percent_nodiploma*)	Data is retrieved from ACS table #B15003	N = 825 Mean = 9.8 Std. dev. = 6.7 Min = 0 Max = 41.9

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