BEFORE THE PUBLIC SERVICE COMMISSION
OF THE STATE OF MISSOURI

In the Matter of Union Electric Company d/b/a	)	
Ameren Missouri's 3rd Filing to Propose	)	File No. EO-2018-0211
Regulatory Changes pursuant to MEEIA.	)	

REBUTTAL TESTIMONY

of

CARA SPENCER

on behalf of

CONSUMERS COUNCIL OF MISSOURI

August 30, 2018

REBUTTAL TESTIMONY

of

CARA SPENCER

Q. PLEASE STATE YOUR NAME AND OCCUPATION.

A. My name is Cara Spencer, and I am the Executive Director of the Consumers Council of Missouri.

Q. WHAT IS YOUR EDUCATIONAL BACKGROUND?

A. I have a Bachelors in Science degree in Mathematics from Truman State University.

Q. WHAT IS YOUR WORK EXPERIENCE?

A. Since 2016, I have served as the Executive Director for the Consumers Council of Missouri. In that role, I have testified in a variety of public hearings, and participated in several policy seminars and workshops related to utility regulatory issues.

I have been actively involved in consumer advocacy on energy policy issues, as well as advocacy on behalf of consumers on a variety of complex regulatory issues, with a particular focus on vulnerable consumers on a local, state, and national level.

A more detailed Curriculum Vitae is attached to this testimony as Attachment A.

Q. WHAT IS THE PURPOSE OF YOUR TESTIMONY?

A. The purpose of this rebuttal testimony is to present issues that Consumers Council believes the Commission should address regarding Ameren Missouri's 3rd filing designed to implement a plan under the Missouri Energy Efficiency Investment Act ("MEEIA"), proposed to be effective starting March 1, 2019 and ending December 31, 2024.

Consumers Council recommends that the Public Service Commission's ("PSC" or "Commission") order Ameren Missouri to begin collecting certain demographic data regarding the availability and use of energy efficiency programs within its service territory.

Consumers Council also recommends that the Commission modify Ameren Missouri's request for a nearly six-year plan so that its MEEIA plan is reviewed in a normal three-years' interval. Circumstances can change too much in three years to delay the requirement for initiating a new case any longer than that.

Q. WHAT DATA DOES CONSUMERS COUNCIL RECOMMEND THAT AMEREN MISSOURI COLLECT AND MAKE AVAILABLE TO THE PUBLIC?

A. As a condition of approval of its 3rd MEEIA plan, Consumers Council proposes that Ameren Missouri collect demographic data showing estimated energy use intensity, energy efficiency equitable baseline investment, and energy savings in Ameren Missouri service territory across various parameters. The goal of this data collection would be to explore residential energy efficiency in order to evaluate the equitable distribution of investments and benefits among Ameren Missouri customers.

This data should be made available to all parties and the general public in order to better inform future energy efficiency discussions and to aid the Commission's decision-making in this area of regulatory policy. Making this data available would allow researchers to analyze the impact of current MEEIA efforts, and it could assist in preparation for its subsequent MEEIA plan application to the Commission.

Ameren Missouri should also be required to collaborate with an independent academic researcher to provide an analysis of the data regarding energy efficiency utilization by customer income level and by other factors.

Q. WHAT SPECIFIC DATA SHOULD BE REQUIRED?

A. Data provided by Ameren Missouri should include, at a minimum, the following:

1) A compilation of annual reconciliation reports (includes annual spending, savings and TRC[1] on all residential and income qualified residential programs) from 2012 to 2017, and for ongoing program years,

2) Any data on energy efficiency program utilization by zip code (i.e., dollars, measures, applications),

3) Aggregate residential consumption data at a spatial level that could be correlated with Census spatial levels (i.e., zip code+4). This includes:

   - Average monthly residential usage for each zip code in the service territory, and

   - A random sample of 2% of household monthly sum usage in each zip code.

[1] Total Resource Cost.

Q. WHAT RESEARCH DELIVERABLES WOULD YOU EXPECT TO BE PROVIDED BY AN INDEPENDENT ACADEMIC RESEARCH AUTHORITY?

A. The data provided by Ameren Missouri would allow the following research deliverables to be performed for the parties and the Commission:

1) Estimate and assess the spatial distribution of mean/median energy use intensity (EUI) in kBTU/ft^2 across the Ameren Missouri service territories. The EUI model and maps may be used for exploring residential energy efficiency disparities across the service territories and for program targeting. This model could be based on 1) 2009 or 2015 data from the Energy Information Administration Residential Energy Consumption Survey[2] or 2) aggregated consumption data from the Ameren with additional parcel data from county tax offices to calculate mean/median square footage.

2) Assess program investments between income-qualified and non-income qualified energy efficiency programs and customers. Establish an Equitable Energy Efficiency baseline (E3b) to quantify the gap between equitable, based on territory population demographics (e.g., the proportion of low-income households), and actual annual investments as reported in annual utility filings with the Missouri Public Service Commission.

[2] Reames, T. G. (2016). Targeting energy justice: Exploring spatial, racial/ethnic and socioeconomic disparities in urban residential heating energy efficiency. *Energy Policy*, *97*, 549-558.

3) Assess the equitable distribution of household energy savings between low-income and non-low-income customers in the service territory based on utility reported data as filed with the Commission for relative comparisons.

Q. ARE YOU AWARE OF AN EXAMPLE OF INDEPENDENT ACADEMIC ANALYSIS PERFORMED ON THE EQUITY OF RESIDENTIAL ENERGY EFFICIENCY UTILIZATION?

A. Yes. I have attached an article by Dr. Tony Reames of the University of Michigan. His 2016 journal article in Energy Policy analyzed data collected from the Kansas City, Missouri area (Attachment B to this testimony).

Q. WHAT IS CONSUMERS COUNCIL'S POSITION ON THE LENGTH OF AMEREN MISSOURI'S PROPOSED MEEIA PLAN?

A. Consumers Council is opposed to this request. Five years and 10 months is too long of a period for any utility's energy efficiency plan to operate without a full review of its MEEIA plan. Ameren Missouri should be required to follow a three-year planning interval, as intended by the Commission's own rules.[3] Further arguments on this issue may be offered by Consumers Council's legal counsel.

The Commission has allowed Ameren Missouri to invest an enormous amount of money through MEEIA and allowed it to charge its electric consumers through an extraordinary single-issue surcharge on bills. There is no reason to further reduce the review that MEEIA projects receive. Cost projections and technological

[3] 4 CSR 240-20.093(a)(5).

developments change rapidly in the area of energy efficiency, and the public deserves to have an opportunity to fully review and comment on the utility's assumptions and to address potential changes at least every three years. PSC commissioners serve for six-year terms; it should be possible for a commissioner serving only one term to able to weigh in on more than just one MEEIA plan for each electric utility in the state.

In order for meaningful public accountability, each utility should be required to initiate a full MEEIA plan on a regular three-year basis and bear the burden of proof to show to the Commission that it will be a just and reasonable plan over the next three years. Ameren Missouri's request of a MEEIA plan covering almost six years would hinder the opportunity for a full and contemporaneous regulatory review.

If the Commission agrees with our recommendation regarding data collection and evaluation, it is particularly important that the public not have to wait six years in order to apply the knowledge gained from that data analysis.

Q. DOES THIS END YOUR TESTIMONY?

A. Yes.

Attachment A

Cara Marie Spencer

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Summary

Several years experience in energy policy, rate cases and program implementation. Work includes advocacy and education of the general public, legislators, and the media. Over a decade of experience in corporate analytics and market analysis including projection modeling and complex market modeling.

Education

Bachelor of Science, Truman State University (2000); Mathematics

Professional Experience

Executive Director of Consumers Council of Missouri ***2016-present***

Chief director of a state-wide non-profit whose mission is to educate consumers and advocate for their collective interests on issues with a focus on utility rates and utility policy. As director, I have testified before both the Missouri State House and Senate and advised legislators on policies before them. I have served as a utility and consumer expert to major Missouri publications including the St. Louis Post Dispatch, St. Louis American, Missouri Times, and several television, radio, online as well as several other print sources.

Alderman, St. Louis City; Ward 20 ***2015-present***

Elected member of the St. Louis Board of Alderman, the City's legislative branch of City government. Successfully led and passed numerous significant pieces of legislation such as the nation's first municipal "Good Samaritan" law, the nation's toughest municipal law regulating payday lending and spearheaded the effort to re-establish an air quality control program to the City. Serves as Vice Chair of the Public Utilities Committee.

Director, Analytics and Epidemiology ; Humanumeric ***2014-2015***

Designer of complex mathematical modeling designed to drive market analytics and facilitate strategic decision making for Fortune 500 companies. Created custom, analytical solutions facilitating assessments of new and existing market opportunities. Streamlined global model updates through building specialized mathematical tools to automate data entry and ensure accuracy.

Director, Analytics and Epidemiology ; The Mattson Jack Group // Tessellon ***2001-2015***

Oversaw the development of custom, complex mathematical models designed to drive strategic decision making for large businesses. Developed several specialized products and custom models designed for long-term strategic planning.

ATTACHMENT B

FOLLOWS THIS PAGE

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Targeting energy justice: Exploring spatial, racial/ethnic and socioeconomic disparities in urban residential heating energy efficiency

Tony Gerard Reames

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HIGHLIGHTS

- Develops statistical model to predict block group (BG) residential heating energy use intensity (EUI), an energy efficiency proxy.
- Bivariate and multivariate analyses explore racial/ethnic and socioeconomic relationships with heating EUI.
- BGs with more racial/ethnic minority households had higher heating EUI.
- BGs with lower socioeconomics had higher heating EUI.
- Mapping heating EUI can facilitate effective energy efficiency intervention targeting.

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ABSTRACT

Fuel poverty, the inability of households to afford adequate energy services, such as heating, is a major energy justice concern. Increasing residential energy efficiency is a strategic fuel poverty intervention. However, the absence of easily accessible household energy data impedes effective targeting of energy efficiency programs. This paper uses publicly available data, bottom-up modeling and small-area estimation techniques to predict the mean census block group residential heating energy use intensity (EUI), an energy efficiency proxy, in Kansas City, Missouri. Results mapped using geographic information systems (GIS) and statistical analysis, show disparities in the relationship between heating EUI and spatial, racial/ethnic, and socioeconomic block group characteristics. Block groups with lower median incomes, a greater percentage of households below poverty, a greater percentage of racial/ethnic minority headed-households, and a larger percentage of adults with less than a high school education were, on average, less energy efficient (higher EUIs). Results also imply that racial segregation, which continues to influence urban housing choices, exposes Black and Hispanic households to increased fuel poverty vulnerability. Lastly, the spatial concentration and demographics of vulnerable block groups suggest proactive, area- and community-based targeting of energy efficiency assistance programs may be more effective than existing self-referral approaches.

1. Introduction

Climate change concerns highlight a number of serious social and environmental inequalities that can be traced to energy consumption. These concerns form the foundation of a growing field of scholarship, and activism, on energy justice. For instance, Hernández (2015) issued "*A Call for Energy Justice*," which acknowledged four basic human rights to energy: the right to a healthy, sustainable energy production; the right to best available energy infrastructure; the right to affordable energy; and the right to uninterrupted energy service. For the many US households suffering in fuel poverty, nearly 14 million with unpaid utility bills and 2.2 million with disconnected utilities, these rights are unfulfilled promises (Seibens, 2013). Fuel poverty (also known as energy poverty or energy insecurity) is the inability of households to afford energy services for adequate heating and cooling resulting in uncomfortable indoor temperatures, material deprivation, and accumulated utility debt (Li et al., 2014, Hernández 2013, Buzar, 2007; Boardman, 2012). More than a matter of mere comfort, indoor temperatures that are too cold in winter or too hot in summer have detrimental mental and physical health impacts, including death, for vulnerable populations like children, the elderly, and racial/ethnic minorities (Anderson et al., 2012; Liddell

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0301-4215/

and Morris, 2010, Howden-Chapman et al., 2009, Howden-Chapman et al., 2007, Klinenberg, 2002; Taylor et al., 2001). A key measurement of fuel poverty is the proportion of gross income spent on home energy costs, or the energy burden. Low-income US households have an average heating energy burden of 4.7% that is more than double the 2.3% national average and more than four times the 1.1% average burden for high-income households (US Department of Health and Human Services [HHS] 2011). Analysts consider a heating energy burden greater than 2% unaffordable (Fisher et al., 2014).

However, fuel poverty is more than a straightforward relationship between household income and energy costs. The concept became prominent in the 1980s and has been well-studied in the UK (see special issue Volume 49 of this journal) and even codified in law with the passage of the Warm Homes and Energy Conservation Act of 2000. Investigations of fuel poverty, including those beyond the UK, demonstrate that a pure financial assessment of its prevalence does not account for the variety of factors and relationships that produce and sustain it. Buzar (2007) advocated a "relational approach" to studying fuel poverty, one that combines understanding energy policy, housing infrastructures, and the lived experience of the fuel poor. Hernandez and Bird (2010) found the incidence of high inner-city energy burdens was due in part to a lack of energy assistance funding, a lack of housing and energy policy coordination, and a lack of understanding the social and economic benefits of energy conservation and efficiency. Harrison and Popke (2011) suggested fuel poverty be understood "as a geographical assemblage of networked materialities and socioeconomic relations" determined by household socioeconomic characteristics, material conditions of the home, and the structure that defines the provision of energy.

The conceptualization of fuel poverty as an energy justice concern speaks to the energy-related distribution, procedure, and recognition of "what constitutes the basic rights and entitlements of sufficient and healthy everyday life" (Walker and Day, 2012). Consequently, fuel poverty violates the basic principle of distributive justice. Distributive justice is the idea that all members of society have the right to equal treatment, and that outcomes should be fairly distributed, and provides moral guidance for the political processes and structures that affect the distribution of economic benefits and burden across and within society (Rawls, 1971; Sen, 1999 Schlosberg, 2013). As a distributive injustice, fuel poverty results from three interconnected inequalities: income inequality, inequality in energy prices, and inequalities in housing and energy efficiency (Walker and Day, 2012). Although fundamentally, fuel poverty is a problem of distributional injustice, its production and persistence are also the result of an injustice in recognition of the specific energy-related needs of vulnerable populations, and procedural injustice related to access to information, meaningful participation in decision-making, and access to legal processes for achieving redress or challenging decision-making processes (Walker and Day, 2012).

Addressing the distributive injustice of fuel poverty requires first determining what should be fairly distributed. Since inequalities in income and energy prices require larger social and economic solutions, residential energy efficiency retrofits have become a key fuel poverty intervention strategy (Howden-Chapman et al., 2007, Howden-Chapman et al., 2009, Bird and Hernández 2012, Gibson et al., 2011, Harrison and Popke, 2011). However, the absence of easily accessible data on individual household energy consumption and efficiency, and an incomplete understanding of the spatial distribution of vulnerability presents an impediment to effectively targeting those most in need (Walker et al., 2013; Sefton, 2002). Recently, scholars have conducted small-scale, area-based studies using readily available public data and geographic information systems (GIS) to offer visualizations of spatial disparities in the distribution of fuel poverty vulnerability and energy consumption to facilitate policymaking and intervention targeting (Pereira and de Assis, 2013; Walker et al., 2013; Fahmy et al., 2011; Morrison and Shortt, 2008).

In the US, while fuel poverty is neither recognized colloquially or politically, a few studies have modeled the spatial distribution of residential energy consumption, including socioeconomic and demographic control variables in their models (Howard et al., 2012; Min et al., 2010; Heiple and Sailor, 2008). Others have explored the socioeconomic and demographic relationships of national residential energy consumption patterns (Health and Human Services [HHS] 2011; Steemers and Yun, 2009; Ewing and Rong, 2008; Adua and Sharp, 2011; Newman and Day, 1975). Generally, these studies concluded that, all else being equal, low-income households consume less energy. This broad assessment of consumption rather than efficiency, tends to mask fuel poverty vulnerability. Instead, when analyzing energy use intensity (EUI), or energy consumption normalized by building square area, as a proxy for energy efficiency, national data from the US Energy Information Administration (EIA) show that low-income household, on average, are less efficient, with an EUI 27% greater than high-income households. The spatial distribution of energy efficiency is further complicated by a persistent system of racial and income residential segregation that defines housing development and consumption patterns in many US metropolitan areas. A substantial amount of research is aimed at understanding the causes and consequences of residential segregation, primarily from the fields of sociology and public health (Sampson, 2012; Sharkey, 2011; Anthopolos et al., 2011; Sampson and Wilson, 1995; Wilson, 1987). But very little of this research is connected to energy-related research in meaningful ways that illustrates the critical importance of place to the presence of energy efficiency disparities and fuel poverty vulnerability.

This paper uses publicly available data to model residential heating energy efficiency, as a function of various housing and household characteristics for a tri-county metropolitan area. The study extends previous energy consumption and social justice oriented research by predicting small-area estimation of end use energy efficiency, and then examining racial/ethnic and socioeconomic relationships. This analysis not only furthers our understanding of the dynamics and distribution of energy efficiency disparities, it has practical applications that may assist policymakers and practitioners with developing and implementing more equitable, efficient, and effective targeting of energy assistance programs and weather-related vulnerability prevention activities. This study seeks to answer two research questions. First, does residential heating energy efficiency vary within a metropolitan area? And if so, what are the spatial characteristics of that variation? Second, what are the patterns of association between residential heating energy efficiency and racial/ethnic, and socioeconomic characteristics? The remainder of the paper summarizes the modeling and mapping of residential heating energy efficiency and analysis of the spatial, racial/ethnic, and socioeconomic patterns. Section 2 describes the study area, and methods for developing a model for heating energy efficiency and small-area predictions. Section 3 presents the results of the geographic and statistical analyses. Section 4 concludes with policy implications.

2. Methodology

2.1. Description of study area

Kansas City is the largest city in the State of Missouri and lies mostly in Jackson, Clay, and Platte counties (see Fig. 1). This tri-county region also represents the service area for United Services,

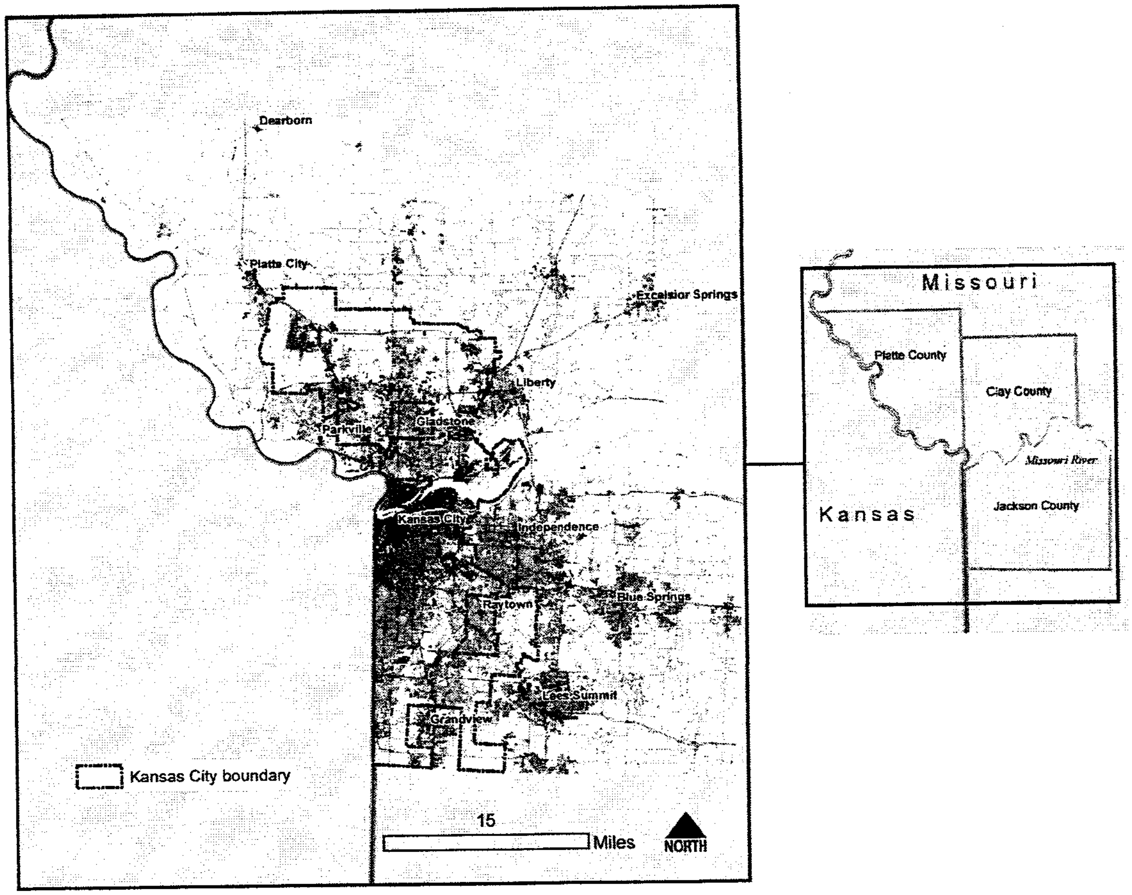

Fig. 1. Study area: Kansas City, Missouri (Jackson, Clay and Platte counties).

one of nation's roughly 1000 Community Action Agencies (CAAs). CAAs are mostly nonprofit, anti-poverty social service organizations covering nearly 96% of US counties. CAAs are responsible for administering federal low-income energy assistance programs, such as, the Department of Health and Human Services Low-income Home Energy Assistance Program which provides utility bill assistance and the Department of Energy Weatherization Assistance Program which provides no-cost energy efficiency retrofits. According to Building America, which determines building practices based on climate zones to achieve the most energy savings in a home, the counties are located in Climate Zone 4, which has a range of 4000–5499 heating degree days (HDDs) annually, and where the average monthly outdoor temperature drops below 47 °F (7 °C) during the winter (U.S. Department of Energy, 2015).[1] Hence, homes in the area exhibit relatively high usage of heating equipment. In fact, space heating accounts for 41% of total household energy consumption in Missouri. The main heating fuel sources are natural gas (52%) and electricity (35%). Overall, the average Missouri household total energy consumption is roughly 100 million BTUs per year, approximately 12% more than the national average (EIA, 2013a).

According to the 2010 decennial census, the counties had a total population of 985,419 in 398,124 households. The area covers urban, suburban, and rural landscapes. In addition to the urbanization gradient, socioeconomic characteristics in the area vary greatly. Median block group income ranged from $14,250 to $154,250. The household racial composition included 77.1% White households, 17.3% Black households, and 5.2% Hispanic households, as identified by the head of household. Kansas City is consistently identified as one of the nation's twenty-five most racially segregated metropolitan areas due to its high placement on a range of housing segregation indices, most recently ranking 23rd based on black-white segregation (Logan and Stults, 2011; Denton, 1994; Massey and Denton, 1993). Kansas City also exhibits a high, and increasing, level of residential segregation by income. According to Pew Research on Social and Demographic Trends, Kansas City's Residential Income Segregation Index score increased from 38 in 1980 to 47 in 2010 (Fry and Taylor, 2012).

2.2. Data

In the absence of detailed individual household energy data, the EIA's Residential Energy Consumption Survey (RECS) provides household-level energy consumption data for a representative sample of occupied, primary residences in the US. The RECS employs a multi-stage area probability design to ensure the selection of a representative sample of housing units, carefully controlled at specified levels of precision, to allow analysis of housing unit characteristics and energy consumption and expenditures at the following geographic levels: national, census region, census division, groups of states within a census division, and individual

[1] Climate zones range from 1 (warmest) to 7 (coldest). Heating degree days (HDDs), commonly used in calculations relating to the energy consumption required to heat buildings, is a measurement of the difference in temperature between the mean outdoor temperature, over a 24-h period, and a given base temperature for if a building's indoor temperature fell below would require heating, typically 65 °F (18 °C) in the US. For example, if the mean outdoor temperature for a day is 35 °F, the HDDs measurement for that day is 65 − 35 = 30. Essentially, areas with a larger number of HDDs have colder outdoor temperatures and require more energy for heating.

states (EIA, 2013b). The RECS, first conducted in 1978, collects data on energy consumption, expenditure and behavior along with a number of household demographics and housing unit characteristics. In the past, the RECS sample size has not been particularly useful for analyzing energy patterns at spatial scales lower than the census region, except for the most populous US states; California, Texas, New York, and Florida. The 13th iteration of the survey, conducted in 2009 and released in 2013, nearly tripled in sample size to 12,083 housing units (up from 4382 in 2005) representing the US Census Bureau's statistical estimate of 113.6 million occupied primary residences. Subsequently, the 2009 RECS allows for additional state-level analysis with the collection of representative samples in 12 additional states, including Missouri. A sample of 686 households were surveyed to represent the 2.35 million occupied housing units in Missouri. For geographic domain estimation purposes, base sampling weights were applied to each housing unit, which was the reciprocal of the probability of selection into the sample and is the number of households in the population each observation represents (EIA, 2013b). Each sampling weight value was used as a weighting factor in the weighted regression model.

Data for spatial modeling and mapping of the study area were obtained from the U.S. Census Bureau 2006–2010 American Community Survey (ACS) 5-year estimates. The census block group was used as the unit of analysis for this research. Census block groups are a contiguous cluster of blocks within a census tract and generally consist of between 600–3000 people. The census block group is the smallest spatial resolution for which household and housing unit characteristics similar to RECS variables are publically available from the U.S. Census Bureau. In addition, it is assumed that physical and social homogeneity are more likely at the smaller block group level than larger spatial levels, such as, census tracts or zip codes. A GIS data layer of census block groups for the study area was created by clipping data from the U.S. Census Bureau TIGER/Line Shapefiles with demographic and economic data from the 2006–2010 ACS 5-year estimates. Block groups were retained for analysis only if data values for both population and number of occupied housing units were greater than zero. Subsequently, 757 of 763 block groups in the three-county study area were included in this analysis.

The RECS microdata set can be used to develop a bottom up statistical model. Bottom up statistical models use input data at a granular level, such as a sample of individual households, for extrapolation to a geographic area of interest. These statistical models have been used to establish relationships between various characteristics of household energy consumption (i.e. specific end use consumption, total consumption, energy use intensity) while controlling for exogenous variables such as housing unit characteristics, household characteristics, urban form and climatic conditions (Min et al., 2010; Ewing and Rong, 2008; Tso and Yau, 2007). Min et al. (2010) developed a statistical framework for modeling residential space heating (and other end use) consumption at a zip code- level resolution using the 2005 RECS microdata. Their results were validated against residential energy sales data. This study extends their framework to estimate residential heating efficiency by creating a state-level regression model using the Missouri sample of housing units in the 2009 RECS microdata set and exploring small-area spatial, racial/ethnic, and socioeconomic patterns. Since many of the variables identified in the RECS can also be found in the Census ACS, relationships derived from the statistical model, known as direct estimators, can be applied to the block group level dataset as indirect estimators for constructing small-area estimates, under the assumption that the small areas have the same characteristics as the large areas (Rao and Molina, 2015). The next two sections detail this process.

2.3. Specifying a robust regression model for heating energy efficiency

The ordinary least square (OLS) method was used to analyze how housing unit and household characteristics influence residential heating energy efficiency. Heating energy efficiency is operationalized as annual heating energy use intensity (EUI). Generally, a lower EUI signifies relatively efficient performance. The EUI is defined as the quantity of energy used in producing a given level of service, expressed as energy consumed per unit of output. The heating EUI (kBtu/m^2) was calculated for each RECS observation by dividing the total annual heating consumption (kBtu) by the housing unit square area (m^2). Trained interviewers use a standardized method for measuring and collecting the dimensions of the housing unit. Total annual heating consumption is the aggregation of a household's space heating consumption from all fuel types (i.e. natural gas, electricity, liquefied petroleum gas (LPG), fuel oil, and/or kerosene). The RECS captures consumption data from actual utility bills. Of the Missouri RECS sample, 676 observations had total annual heating consumption greater than zero kBtu. Another observation was dropped as it was the only housing unit in the sample reporting fuel oil/kerosene as the primary heating source. Fuel oil/kerosene are not major sources of heat in the tri-county area; only 0.09% of homes use fuel oil/kerosene as their primary heating source (US Census 2016). Upon testing for outliers, an additional observation was dropped that exhibited an extremely high EUI for a relatively small footprint. The final data set consisted of a sample of 674 Missouri housing units.[2]

The OLS model can be formulated as,

$$\ln E = \beta_0 + \sum_{i}^{n} \beta_i * \chi_{i,RECS} + \varepsilon$$

where E is the annual heating EUI, and $\chi_{i,RECS}$ is the predictor variable χ_i from the RECS dataset (Min et al., 2010). The dependent variable was natural logged to better fit the nonlinear relationship between heating EUI and the independent variables (Min et al., 2010; Ewing and Rong, 2008).

Since many of the predictors of heating EUI are themselves correlated, it is important to consider their simultaneous effects using multivariate analysis techniques. This approach therefore requires determining the best subset of predictors of heating EUI. Initial selection of independent variables was guided by previous studies using OLS to understand residential energy consumption. The two major themes on factors that contribute to residential energy consumption are categorized as the physical-technical-economic model (PTEM) and the lifestyle and social-behavior tradition (LSB) (Adua and Sharp, 2011). Many models include variables from the PTEM perspective which explains energy consumption as a result of housing unit characteristics, or the building's physical structure and equipment characteristics, and economic and environmental factors. These variables include: type of home, year home built, home size, household income, price of energy, geographic location, and climate variables (Ewing and Rong, 2008; Min et al., 2010; Adua and Sharp, 2011, Valenzuela et al., 2014). The LSB tradition draws on the importance of human occupants to energy consumption, or household characteristics. LSB-related variables often include: race/ethnicity, household size, age of householder, and sex of householder (Ewing and Rong, 2008; Min et al., 2010; Adua and Sharp, 2011, Valenzuela et al.,

[2] A sample size of 674 can predict with accuracy at a 95% confidence interval and ± 4 confidence level, for 2,339,684 housing units (population size). Based on the assigned sampling weights, the final sample represents 2,286,868 housing units.

Table 1
OLS regression model for small-scale heating EUI estimation.

DV = ln (EUI_{heat})	Coeff.	Robust Std. Err.
Type of Housing		
Multi-Family	Reference	
Mobile Home	0.68***	0.09
Single Family Dettached	–	
Single Family Attached	–	
Decade Constructed		
Before 1950	Reference	
1950s	–	
1960s	-0.24***	0.07
1970s	-0.18**	0.07
1980s	-0.34***	0.08
1990s	-0.26***	0.07
2000s	-0.29***	0.07
Primary Heat		
Natural Gas	Reference	
Electricity	-1.10***	0.05
Wood	-2.07***	0.23
Liquid Petroleum Gas	–	
Control Variables		
Household Income	-0.03*	0.01
Home ownership	-0.15**	0.05
No. of rooms	-0.09***	0.01
Model Statistics		
Intercept	6.57***	0.08
N	674	
F (11, 662)	85.9***	
Adjusted R^2	0.62	
RMSE	0.523	

-dropped from stepwise regression
* Significance $p < 0.05$.
** Significance $p < 0.01$.
*** Significance $p < 0.001$.

2014). For this model, variables representing housing unit characteristic included three dummy-coded variables for housing type (mobile home, single family detached, and single family attached, with multifamily as the reference category), six dummy-coded variables for decade constructed (1950s through 2000s, with homes built before 1950 as the reference category), and three dummy-coded variables for primary heating fuel (liquid petroleum gas (LPG), electricity, and wood, with natural gas as the reference category). Household characteristic variables included one interval variables for number of rooms, one categorical variable for household income (divided into eight categories), and one dummy-coded variable for home ownership coded as "1", otherwise "0". Final model selection of independent variables was based upon backward stepwise selection.

2.4. Utilizing census data for small area heating EUI estimation

Since the goal of this study is to explore heating energy efficiency at a geographical domain smaller than the RECS microdata (collected with adequate precision at the state-level), the second step involves using the model above to estimate and map heating EUI for Kansas City. This technique, known as small-area estimation, combines individual level data (i.e. household surveys) and spatial characteristic estimates (i.e. Census data). There have been significant theoretical advances in small-area estimation methodologies for modeling and mapping (Fay and Herriot, 1979; Fahmy et al., 2011; Rao and Molina, 2015). To accomplish this, resultant weights derived from the regression model are applied to spatial data (e.g., housing units by type, housing units built in each decade, housing units using each fuel type for heating, median household income), from the US Census 2006–2010 ACS 5-year estimates. The derived regression weights are therefore intended to reflect the observed pattern of influence at the household level, which is essential to the small area estimation. Regression coefficients β_i are applied to block group level data, $\chi_{i,CENSUS}$, for each of the 757 block groups in the study area (Min et al., 2010), using ARCMap (v.10.3.1) software (ESRI, Inc) to predict block group level heating EUI estimates $\hat{E}$:

$$\hat{\ln}E = \hat{\beta}_0 + \sum_i \hat{\beta}_i * \chi_{i,CENSUS}.$$

Since this modeling approach involves matching two different datasets (RECS and ACS), these sources must first be harmonized with respect to their measurement and weighting. Each census variable was weighted by the percentage (or ratio) of its presence in the Census block group. For example, if the number of housing units heated by electricity in census block group 1 is 100 and the block group has 200 housing units, the variable is standardized as 100/200=0.5, which is comparable to the binary variable for whether or not an observation in the RECS data set uses electricity as its primary heating source. The ratio for each block group is then multiplied by the coefficient for electricity from the regression model.

Lastly, to simply exponentiate the log-linear model, $\hat{\ln}E$, will systematically underestimate the expected value of EUI, thus the scaling value $exp\left(\frac{RMSE^2}{2}\right)$ is needed (Wooldridge, 2009: 211). RMSE is the root mean square error of the model. From the estimated log values $\hat{\ln}E$, the actual estimated EUI is obtained by the equation

$$\hat{E} = \exp\left(\frac{RMSE^2}{2}\right) * \exp(\hat{\ln}E).$$

2.5. Statistical analysis

The relationships between the predicted mean block group heating EUI and measures of race/ethnicity, and socioeconomic status are examined using bivariate and multivariate analyses. First, correlation analysis was conducted between heating EUI and demographic and socioeconomic characteristics. Next multivariate regression was used to explore the relationship between predicted heating EUI and block group racial/ethnic and socioeconomic characteristics. Lastly, logistic regression was used to model how the proportion of racial/ethnic minority headed households, and other block group socioeconomic characteristics affect the probability of block group vulnerability, thus prime for energy efficiency intervention targeting.

3. Results

The final regression model for estimating annual heating EUI, expressed as natural log, is presented in Table 1. The final model consisted of 11 statistically significant variables representing housing unit type, decade housing unit was constructed, primary heating fuel, and control variables for household income, home ownership, and housing unit size. The model explained a considerable proportion of variability in heating EUI (R^2=0.62, F(11, 662)=85.9, $p < 0.001$). Based on the F value of the model, the final sample size of 674 is large enough to make the model significant. Cross-sectional studies are at greater risk of exhibiting heteroskedasticity. Weighted regression is one method to correct residuals and the model's residual versus fit plot exhibits a constant variance and shows no evidence of heteroskdasticity. Additionally, robust standard errors were used and are reported in Table 1

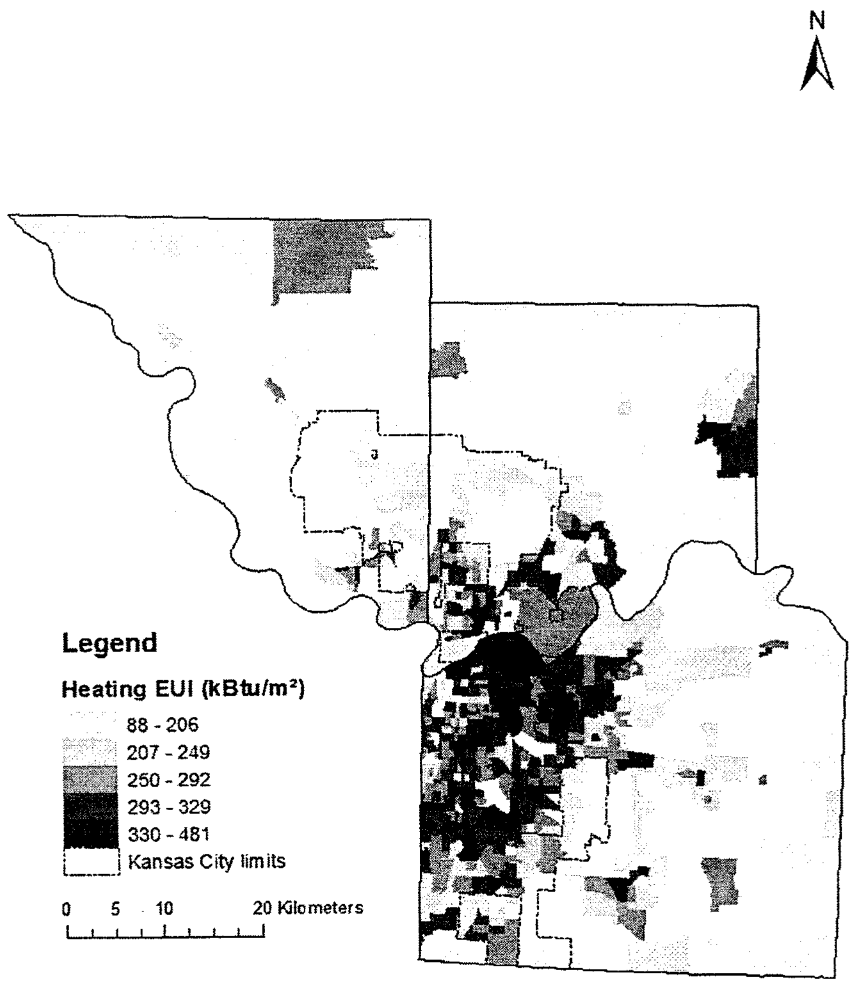

Fig. 2. Predicted block group mean annual heating EUI (kBtus/m^2).

(Wooldridge, 2009). Multicollinearity can also be a major problem for statistical models of residential energy use, and can result in poor predictions of certain end uses (Swan and Ugursal, 2009). Multicollinearity commonly arises with variables that tend to be correlated, such as household income and housing unit size. However, correlations between any two variables in the final model did not exceed 0.45, and the variance inflation factor is 1.32. Thus, the model did not indicate a noticeable presence of multicollinearity.

Fig. 2 illustrates the spatial distribution, in quintiles, of the predicted mean annual heating EUI for each block group, darker shading represents higher predicted heating EUI. The six uninhabited block groups were left uncolored. It is important to note that predicted values reflect the mean heating EUI of all housing units in the block group rather than any specific house (Min et al., 2010). Among the 757 block groups there was significant difference in values of heating EUI, ranging from 88 to 481 kBtus/m^2. The metropolitan mean heating EUI, 269.6 kBtu/m^2 (SD=66.7 k/Btus/m^2), was higher than the state mean heating EUI, 218.9 kBtus/m^2. The heating EUI variation, nearly 400 kBtus/m^2, is quite large. This means that within the same metropolitan region, homes in some areas were far less efficient than others. While block groups with higher heating EUIs are scattered throughout the three counties, the majority of block groups with the highest EUIs were concentrated within the Kansas City limits and its urban core. Of the 151 block groups with the highest (fifth quintile) predicted heating EUI, 119 (78.8%) were located within the city limits.

Table 2
Pearson's correlation between race/ethnicity, socioeconomics and predicted heating energy use intensity (EUI).

Category	Description	Pearson's correlation
Economic status	Median household income	-0.62
	Percent households below poverty level	0.47
Education	Percent population with less than high school diploma	0.51
Age	Percent households with householder aged 65+	0.12
Race/Ethnicity	Percent white householders	-0.37
	Percent black householders	0.32
	Percent Hispanic householders	0.31
Tenure	Percent renters	0.40

All coefficients significant at $p < 0.001$

Pearson correlations, shown in Table 2, revealed statistically significant relationships between socioeconomics, race/ethnicity and predicted heating EUI ($p < 0.001$). Heating EUI is positively correlated with block groups with a higher number of adults without a diploma (0.51), higher number of households in poverty (0.47), more renters (0.40), more Black householders (0.32), more Hispanic householders (0.31), and more senior householders (0.12). Furthermore, heating EUI was negatively correlated with median household income (-0.62) and percentage of White

Table 3
Relationship between estimated heating EUI and block group race/ethnicity, segregation and socioeconomic characteristics.

	Model 1 b	S.E.	Model 2 b	S.E.	Model 3 b	S.E.	Model 4 b	S.E.
Percent black householders	0.75^{***}	0.07	0.19^{*}	0.09				
Percent Hispanic householders	2.58^{***}	0.29	0.71^{*}	0.32				
Percent households below poverty level			1.24^{***}	0.20				
Percent population with less than high school diploma			1.47^{***}	0.28				
Percent households with householder aged 65+			0.75^{***}	0.17				
Black residential segregation					90.93^{***}	7.19	37.09^{***}	9.19
Hispanic residential segregation					238.68^{***}	22.03	94.27^{**}	29.92
Proportion households below poverty level							98.37^{***}	22.87
Proportion population with less than high school diploma							146.14^{***}	29.97
Proportion households with householder aged 65+							64.32^{***}	16.89
Intercept	240.13^{***}	3.29	210.56^{***}	4.75	232.34^{***}	3.39	210.09^{***}	4.82
N		757		757	757			757
R^2		0.21		0.33	0.23			0.33

* Significance $p < 0.05$.
** Significance $p < 0.01$.
*** Significance $p < 0.001$.

householders (−0.37). Thus, census block groups with lower socioeconomics, lower median household incomes, and higher percentages of Black or Hispanic households are more likely to have higher heating EUIs. Additionally, Kruskal-Wallis tests were conducted to determine if heating EUI was different among block groups divided into quintiles by the socioeconomic and race/ethnicity variables of interest. Individual Kruskal-Wallis tests showed there were statistically significant differences in heating EUI between the quintiles of median household income (χ^2=330.9), percent poverty (χ^2=171.1), percent less high school education (χ^2=195.2), percent senior headed households (χ^2=20.2), percent renters (χ^2=168.2), percent White householders (χ^2=78.1), percent Black householders(χ^2=97.2), and percent Hispanic householders (χ^2=94.7), (DF=4, $p < 0.001$).

Regression models examining how race/ethnicity are related to heating EUI are shown in Table 3. Model 1 in Table 3 shows this relationship when socioeconomic characteristics of the block group are not taken into account. This model reveals a strong relationship between race/ethnicity and heating EUI. The model shows that as the percentage of Black households and Hispanic households in a block group increase, heating EUI increases by 0.75 and 2.58 kBtu/m^2, respectively.

The second model in Table 3 (Model 2) shows how race/ethnicity are related to heating EUI when the effects of socioeconomic characteristics of the block group (percent poverty, percent less than high school diploma and percent senior householders) are held constant. In this model, while the positive relationship between race/ethnicity and heating EUI remain, as in Model 1, the effects are moderated by the socioeconomic characteristics of the block group with percent of households below poverty, percent of population with less than a high school diploma, and percent senior headed households having a larger effect on heating EUI, 1.24 (t=6.3), 1.47 (t=5.4), and 0.75 (t=4.5) kBtu/m^2, respectively. After controlling for socioeconomics, the effect of a percent increase in Black or Hispanic households increasing a block group's heating EUI drops to 0.19 (t=2.2) and 0.71 (t=2.2) kBtu/m^2, respectively.

The final two models reported in Table 3 (Models 3 and 4) exchange the percentage of Black and Hispanic households in the block group with a measure of the block group's level of Black and Hispanic racial residential segregation (RRS). The RRS, a measure of the geographic isolation of race/ethnicity from other racial groups (Massey and Denton, 1993, Reardon and O'Sullivan, 2004, Anthopolos et al., 2011). RRS has received increased attention as a major social determinant in poor outcomes (i.e. health effects) and may be a proxy for concentrated neighborhood disadvantage, including exposure to socio-physical environmental stressors in the built environment (Anthopolos et al., 2011). Model 3 shows that RRS has a strong positive relationship with heating EUI. Each unit increase in Black isolation increases heating EUI by roughly 91 kBtu/m^2. Hispanic isolation has an even greater effect on heating EUI. Every unit increase in Hispanic isolation increases heating EUI 239 kBtu/m^2. In Model 4 the relationship between segregation and heating EUI remains strong even after controlling for the socioeconomic characteristics of the block group. Given that the isolation index is a value between 0 and 1, the socioeconomic block group characteristics in Model 4 are in proportions rather than percentages. The Black and Hispanic isolation indexes maintain a strong positive relationship with heating EUI but are slightly moderated by block group socioeconomic characteristics. Once socioeconomic characteristics- poverty (t=4.3), less high school (t=4.9), senior households (t=3.8)- are taken into account, the effect that a unit increase in Black and Hispanic isolation increases heating EUI drops to 37 (t=4.0) and 94 (t=3.2) kBtu/m^2, respectively.

Fig. 3 illustrates the spatial distribution of high-risk block groups, which would be prime candidates for energy efficiency interventions. High-risk block groups are defined as those where predicted heating EUI was greater than study area mean (269.6 kBtu/m^2), median year home built was less than the study area mean (1966.5), and median household income was less than the study area mean ($51411.50). There were 263 block groups meeting these criteria (34.7% of block groups). More than a quarter of the area's population (26.6%) resided in high-risk block groups. The racial composition included 49.7% of the Black population, 46.9% of the Hispanic population, and 18.7% of the White population. Black and Hispanic households within the high-risk block groups are highly overrepresented compared to their representation within the entire study area (29.6% Black, and 8.6% Hispanic), while White households are underrepresented (62.4%). If there were no disparities in heating EUI this would not be the case.

To understand the odds that the racial/ethnic and socioeconomic characteristics of a block group contribute to that block group's likelihood of being high-risk, logistic regression results are presented in Table 4. Table 4 suggests that a 10% difference in percent households in poverty increased the odds by 2.7% ($p < 0.01$) that the block group is high-risk. Racial/ethnic characteristics (percentages of Black and Hispanic households) are significant predictors of high-risk block groups ($p < 0.001$). For instance, a 10% increase in Hispanic households increased the high-risk odds by a factor of 10.8. Logistic regression results showed that high-risk block groups are poorer, have less educational attainment, have more households headed by seniors, and

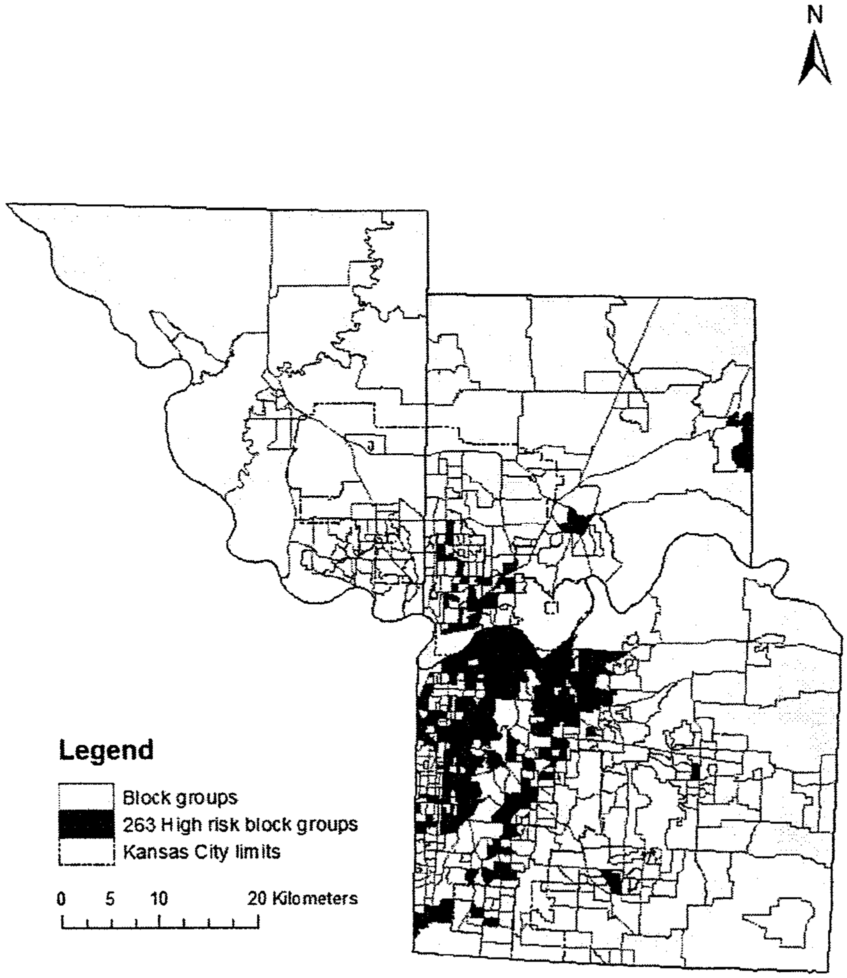

Fig. 3. High-risk block groups. High-risk block groups are defined as those where heating EUI, median age of home, and median household income were worse than the study area average. There are 263 high-risk block groups identified.

Table 4
Logistic regression – high-risk block groups.

	Odds ratio	S.E.
Percent black householders	1.014***	0.004
Percent Hispanic householders	1.079***	0.023
Percent households below poverty level	1.027**	0.010
Percent population with less than high school diploma	1.050***	0.013
Percent households with householder aged 65+	1.021**	0.008
Intercept	0.060***	
Pseudo R^2	0.24	
N	757	

*Significance $p < 0.05$
** Significance $p < 0.01$.
*** Significance $p < 0.001$.

have greater percentages of Black and Hispanic households.

4. Conclusion and policy implications

This study estimated the mean heating EUI for 757 census block groups in Kansas City, Missouri (Jackson, Clay, and Platte counties). The findings demonstrate that disparities exist in the relationships between the spatial, racial/ethnic, and socioeconomic characteristics of census block groups and the estimated mean block group heating EUI (kBtu/m^2), a proxy for energy efficiency where a higher EUI signals relatively less efficiency when compared to similar sized homes. Predictions reveal that block groups with lower median incomes, a greater percentage of households below poverty, a greater percentage of racial/ethnic minority headed households, and a larger percentage of the population with less than a high school education experienced higher mean heating EUIs. Essentially, homes in block groups exhibiting these demographic and socioeconomic characteristics are more likely to be less energy efficient when compared to other block groups in the region.

This analysis also reveals an association between the enduring effects of residential racial and income segregation and the distribution of residential energy disparities. The figures above illustrate that past institutionalized residential segregation continues to influence urban housing consumption and translates directly to energy-related disparities. Urban sociologists often associate residential segregation with concentrated social and economic disadvantage (Sharkey, 2013; Sampson, 2012; Klinenberg, 2002). The results of this study follow decade-old reports by two major African American organizations about the relationship between Blacks, energy and climate change. Both the Congressional Black Congress Foundation and the American Association of Blacks in Energy released reports in 2004 assessing the disproportionate effects of energy inequities on Blacks. Since these reports, there has been little research conducted on this issue and virtually no policy advances. Recognizing that the uneven development patterns and high levels of residential segregation evident in Kansas City occur in other US urban areas, such as St. Louis and Detroit, this study should be replicated to explore if similar energy disparity patterns exist and determine the need for a national urban energy justice policy.

Space heating remains the largest, single end use, accounting for 41% of residential energy consumption (EIA, 2013c). Modeling the efficiency of residential space heating (and cooling) is important because of its responsiveness to weather. Prioritizing heating energy efficiency and targeting building envelope retrofits, before appliance and lighting efficiency, may have greater potential as the lifespan of a housing unit most likely outlasts the current occupant and appliances. Additionally, in dominant discussions on climate change, global warming specifically, winter weather and cold conditions receive far less attention. Nevertheless, recent studies have found that the effects of global warming (i.e. the loss of Arctic sea ice) can be linked to extreme and prolonged cold weather patterns in mid-latitudes, such as the cold spells experienced by northeastern and Midwestern states during the polar vortex of winter 2014.(Peings and Magnusdottir, 2014, Tang, 2013, Francis and Vavrus, 2012). Subsequently, as climate change adaptation discourse becomes more prevalent, it is necessary to understand the material experience of changing environmental conditions, the effect on everyday life, and the potential ways in which communities are threatened (Schlosberg, 2013).

Furthermore, energy related disparities increase the sensitivity of low-income and other vulnerable households to extreme temperature exposure resulting in detrimental health implications (Noe, Jin and Wolkin, 2012; Centers for Disease Control [CDC], 2006; Taylor et al., 2001). The Centers for Disease Control (CDC) found that between 2006 and 2010, 63% of weather-related deaths were attributed to extreme cold exposure, compared to 31% attributed to heat-related causes (Berko et al., 2014). Weather-related death rates varied by age, race/ethnicity, sex, location, and income (Berko et al., 2014). For vulnerable populations like the elderly, extremely cold temperatures can be deadly, even indoors. Elderly patients admitted to the intensive care unit for hypothermia are more severely affected and die more frequently when found indoors compared to those found outside with equivalent body temperatures (Mégarbane et al., 2000). In another study, almost half of hypothermia-related deaths occurred indoors, with death rates particularly high among Blacks aged 80 years or older (Taylor et al., 2001). Despite these findings, there is a lack of recognition of the magnitude of problems associated with dangerous indoor temperatures when homes are not adequately heated. Instead, public health agencies often issue broad cold-weather injury risk reduction precautions primarily focused on outdoor protection, like layering clothes and keeping emergency kits and blankets in the car (CDC, 2006). Mapping heating energy efficiency can be combined with hypothermia health data for additional analysis on the connection between efficiency and winter-related injuries and death.

To the disadvantage of the millions of Americas who struggle to access and maintain affordable heating energy services, the consequence of not identifying distinct forms of social inequality in residential energy efficiency means more broad-based energy policies that fail to serve those with the greatest need. For instance, the passage of the 2009 economic stimulus bill created various residential energy efficiency programs across the country. Most programs, however, were market-based interventions in the form of low-interest loans and tax rebates which limited participation by low-income households who often lack adequate credit worthiness to qualify for loans and rarely earn enough annual income to file for tax rebates. Although $5 billon was committed to the Department of Energy's Weatherization Assistance Program, the rollout was slow and inconsistent (Grunwald, 2012). In part, the lack of comprehensive accounting of local energy consumption and efficiency disparities, forced weatherization agencies to rely on prevailing practices of first-come, first-served self-referral operating procedures (Fuller et al., 2010; Madrid and James, 2012). A growing body of research demonstrates that the spatial concentration of fuel poverty risk factors, justifies taking proactive, targeted, area- or community-based approaches for implementing energy assistance programs to overcome participation barriers, including those that are social and cultural, and to more efficiently and effectively deliver services in vulnerable communities (Reames, 2016; Walker et al., 2013; Hallinan et al., 2012).

Moreover, modeling energy use intensity rather than total energy consumption provides more meaningful information for analyzing disparities and targeting the most appropriate intervention to the appropriate location. The residential sector has made energy efficiency progress, continuing a three-decade decline in average consumption per home even as the number and average size of housing units increase. This trend is primarily a result of efficiency improvements for newer homes. While aggregate residential sector statistics and analyses are useful for policy and program development, they often mask the heterogeneity of energy users, resulting in a lack of equity considerations. The use of bottom-up statistical models and mapping, extrapolated to smaller-scale spatial areas allows a more nuanced analysis of energy consumption. While several energy-mapping projects are in various stages of development and implementation across the nation (e.g., Twin Cities Energy Mapping Tool in Minnesota), a barrier to more of these projects remains the proprietary nature of individual energy data, as utilities express concerns about customer privacy, or have little incentive to participate in projects that have the potential reduce revenue. In the meantime, using readily available public data and the methodological procedures presented in this study, offer an alternative for community energy mapping when local utility energy data are unavailable.

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BEFORE THE PUBLIC SERVICE COMMISSION
OF THE STATE OF MISSOURI

In the Matter of Union Electric Company d/b/a	)	
Ameren Missouri's 3rd Filing to Propose	)	File No. EO-2018-0211
Regulatory Changes pursuant to MEEIA.	)	

AFFIDAVIT OF CARA SPENCER

I, the undersigned, being duly sworn, states that my name is Cara Spencer and that the foregoing Rebuttal Testimony of Cara Spencer, including attachments, was prepared by me on behalf of the Consumers Council of Missouri. This testimony was prepared in written form for the purpose of its introduction into evidence in the above utility case at the Missouri Public Service Commission.

I hereby swear and affirm that the attached testimony is true and correct to my best knowledge, information, and belief, and I adopt said testimony as if it were given under oath in a formal hearing.

Cara Spencer

Subscribed before me on this 30th day of August, 2018:

EMILY ANN HOOD
Notary Public
Commission # 16544453
St. Louis County
Notary Seal
STATE OF MISSOURI
My Commission Expires 01-27-2020

Emily Ann Hood
08/30/2018