Title
On the Complexity of Energy Consumption: Human Decision Making and Environmental Factors

Author
Cho, Jaewoo

Publication Date
2018

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA,
IRVINE

On the Complexity of Energy Consumption:
Human Decision Making and Environmental Factors

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Planning, Policy, and Design

by

Jaewoo Cho

Dissertation Committee:
Associate Professor Jae Hong Kim, Chair
Professor Victoria Basolo
Associate Professor Douglas Houston

2018

TABLE OF CONTENTS

Page

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

I would like to express the deepest appreciation to God, my wife Eunhye, and my son Mingyeom, who always support me with endless love, encouragement, and patience. Without their help, I could not finish this hard journey in my life. I also would like to thank my advisor, Professor Jae Hong Kim, and committee members, Professor Victoria Basolo and Douglas Houston. Their academic supports and disciplines have greatly prepared me to become an independent researcher.

CURRICULUM VITAE

Jaewoo Cho

EDUCATION

University of California, Irvine — 2018
Ph.D. in Urban Planning and Public Policy
Dissertation: "On the Complexity of Energy Consumption: Human Decision Making and Environmental Factors"

Seoul National University — 2012
Master in City Planning

Seoul National University — 2006
Bachelor in Landscape Architecture

PROFESSIONAL EXPERIENCE

Research Assistant

Institute of Transportation Studies, UC Irvine
Beyond the Half-Mile Walking Distance Buffer: The Impact of Transit Investment on Broader Vicinity Areas — 2017

University of California Transportation Center Research Project — 2015
Infill Dynamics in Rail Transit Corridors: Challenges and Prospects for Integrating Transportation and Land Use Planning

National Science Foundation Award 1114931 — 2013
Political Fragmentation in Local Governance and Water Resource Management

Graduate School of Environmental Studies, Seoul National University — 2007
Regional Development Method of Janghang County Based on Expert Panels' Opinions

Internship

GIC (Government of Singapore Investment Corporation) — 2008
Part-time researcher in analysis of the spatial structure of Seoul

TEACHING EXPERIENCE

Teaching Assistant	2014 - 2017
Water Resource Policy	Winter 2017
Quantitative Analysis for Planners	Winter 2017
Data Analysis	Fall 2016
Urban Economic Development Policy	Spring 2016
Microeconomics for Urban Planning	Winter 2016
Urbanization and Social Change	Fall 2014
Urban Economic Development Policy	Spring 2014
Environmental Analysis and Design	Winter 2014

Guest Lecture

Using Census Data with Spreadsheets — 2017
Presented at the Urban Studies Student Association Workshop

PUBLICATIONS

Kim, J. H., Cho, J., & Keane, T. D. (2015) Political fragmentation and land use changes in the Interior Plains. *Population and Environment*, *37(1)*, 63-82.

Cho, J., Kim, J. H., & Kim, Y. (2018) Metropolitan governance structure and growth-inequality dynamics in the United States. *Environment and Planning A* (under revision)

PRESENTATIONS

Jaewoo Cho (2017), "Urban form and residential energy consumption: exploring the seasonal variation of the relationship in Chicago", Presented at the 57th Association of Collegiate Schools of Planning Conference

Jaewoo Cho and Jae Hong Kim (2015), "Renewable energy system adoption and the principal-agent problem", Presented at the 62nd North American Regional Science Council Conference

Jae Hong Kim and Jaewoo Cho (2013), "Investigating the dynamics of metropolitan growth - inequality nexus", Presented at the 60th North American Regional Science Council Conference

Jaewoo Cho (2011), "The impact of the capital expenditure proportion on economic growth in local Korean municipalities", Presented at the 22nd Pacific Regional Science Conference Organization

ACADEMIC AND BOARD SERVICE

Co-representative, Ph.D. Student Representative, Planning Policy and Design, University of California Irvine — 2017

Reviewer, Transportation Research Board 97th Annual Meeting (Artificial Intelligence and Advanced Computing Applications Section) — 2017

Conference Session Discussant, "Do state tax breaks for land conservation work?", 62nd North American Regional Science Council Conference — 2015

GRANTS AND FELLOWSHIPS

Social Ecology Dean's Dissertation Writing Fellowship — 2017

Social Ecology Fellowship — 2012

ABSTRACT OF THE DISSERTATION

On the Complexity of Energy Consumption:
Human Decision Making and Environmental Factors

By

Jaewoo Cho

Doctor of Philosophy in Planning, Policy, and Design

University of California, Irvine, 2018

Associate Professor Jae Hong Kim, Chair

Given our rapidly changing society, the complexity of residential energy often hinders the efficacy of energy conservation policies designed to address our current social and environmental problems. Therefore, understanding this complexity appears to be essential to successfully building and efficiently implementing energy policies. The present dissertation attempts to advance our understanding of the dynamics and complexity of residential energy consumption by investigating various determinants and contextual factors through the three interrelated pieces of applied research. Using American Housing Survey (AHS) data, the first study investigates the dynamics of residential energy consumption at the micro level. It is found that the electricity consumption of households who have moved into new homes is generally lower than average, and their consumption is found to increase as the period of residence increases. The second study examines the relationship between the choice of energy-efficient systems and inter-agent dynamics. By employing a logistic regression model with two national datasets, the Residential Energy Consumption Survey (RECS) and the American Community Survey Public Use Microdata Sample (ACS PUMS), the empirical analysis reveals statistically

significant differences in the installation of solar energy systems among households with different degrees of two major inter-agent issues—split incentives and split decision-making problems. The last study focuses on the complexity of residential energy consumption relevant to the surrounding environments, and it pays special attention to seasonality. Based on city-wide data from Chicago and using a special econometric model, the empirical analysis reveals the seasonal dynamics between urban forms and residential energy consumption. Through these three empirical studies, this dissertation explores the dynamics of residential energy consumption in various dimensions and reveals the complicated mechanisms that determine residents' choices with respect to energy consumption. The evidence from this study is especially important because it reinforces the conclusion that there is no panacea when addressing energy issues. This study suggests that policy-makers and planners should instead thoroughly understand a wide range of contextual factors and their influences in order to develop more effective, context-specific energy policies that best fit each distinct geographical and socio-economic situation.

.

INTRODUCTION

Energy is a fundamental and essential element of our society. From the trappings of economic prosperity, such as skyscrapers, telecommunications, and international travel, to the miscellaneous activities that fill people's daily lives – from cooking breakfast to reading books at night – almost all human activities are highly dependent upon energy. However, energy consumption and dependence have also created enormous challenges, such as the Great Smog of London, oil crises, and acid rain, just to name a few. Furthermore, rapidly increasing energy consumption is becoming a serious threat to human well-being and even to human existence. Burning fossil fuels emits greenhouse gases, which results in the degradation of the atmosphere, the acceleration of climate change, and rising sea levels. According to Weart (2008), if current trends continue, sea levels are expected to rise by 56 to 200 centimeters over the next century, resulting in the disappearance of a substantial amount of land.

To cope with these challenges, considerable international attention and efforts over the past two decades have focused on worldwide cooperation. In December 1997, in the first significant global gathering of nation-states dedicated to addressing climate change, 156 countries ratified the Kyoto Protocol, a binding treaty stipulating the reduction of greenhouse gas emissions below the 1990 level. The Kyoto Protocol prompted participating countries to improve their energy efficiency and to decrease their total energy consumption, especially their consumption of fossil fuels. Following the Kyoto Protocol, the next significant international agreement, the Copenhagen Accord of 2009, stated that the increase in global temperature should not exceed 2.0°C above its preindustrial level. Parallel to these efforts, the U.S. has also made climate change and pertinent energy consumption issues high priorities, even though there has recently been a shift in the stance of the administration. Specifically, the U.S. first enacted corporate average fuel economy (CAFE) standards in 1975 to regulate minimum vehicle fuel efficiency and to spur fuel-saving technologies. The U.S. has also allocated a significant amount of its federal expenditures to improving energy efficiency and to inventing alternative energy technologies—in 2012, the U.S. had invested 1.8 billion dollars, and in 2014, 2.8 billion dollars, which is 10% of the total annual expenditures of the Department of Energy—and this trend is increasing.

Despite these efforts, energy consumption has continued to increase. The world's energy consumption rose from 185 quadrillion British thermal units (BTUs) in 1973 to 372 quadrillion BTUs in 2015, and it is expected to reach 814 quadrillion BTUs by 2050 (IEA, 2017; EIA, 2017a). In the U.S., total energy consumption has also increased – from 76 to 97 quadrillion BTUs during the same 1973 to 2015 period (EIA, 2017b). Compared to population or housing unit growth during the same period, both of which are approximately 40%, this increase – at first glance – seems moderate. However, considering the many improvements in building insulation technologies, as well as the higher efficiencies of heating, cooling, and other major appliances, the increased consumption in the residential sector over the past decades implies that efforts to conserve energy in residential sectors through technological advancement have actually been in vain.

While technological advancements in home appliances and residential buildings does lead to greater energy efficiency, this can actually lead residents to consume more energy by making them less concerned about energy costs. Consequently and ironically, the benefits of higher energy efficiencies lead to higher levels of energy consumption, the so-called rebound effect (Berkhout et al., 2000; Greening et al., 2000). In addition to this well-known phenomenon, there are many complicated aspects of residential energy consumption that are intertwined with various behavioral, social, economic, and environmental elements (e.g., Sonderegger, 1978; Murtishaw and Sathaye, 2006; Ko, 2013).

This complexity is one of the major hurdles that impedes the effectiveness of energy policies in coping with the environmental and social problems we are currently facing. Without a thorough understanding of the complexity of residential energy consumption, even well-intended policies may yield unexpected and often negative consequences, implying that understanding this complexity is crucial to successfully building and efficiently implementing residential energy policies. Although considerable efforts have been devoted to understanding the nature of residential energy consumption, our knowledge base regarding its complexity is still limited. To advance our understanding, this dissertation investigates how the complexity associated with residential energy consumption produces dynamics that change the nexus between energy consumption and its various determinants. The dissertation pursues this aim through the following three interrelated studies:

(1) The first study, titled "The Micro-level Dynamics of Residential Electricity Consumption," empirically investigates the effect of the residence period on energy consumption patterns by employing a fixed-effect panel regression model. Specifically, using AHS data from 2001 to 2013, this study analyzes the association between the household's period of residence and its electricity consumption level. Additionally, the study also examines how various determinants of energy consumption – through their interactions with the residence period – have different impacts over time.

(2) The second study, titled "Barriers to Adoption of Solar Energy Systems: Split Incentives and Complications in Decision-Making", focuses on complicated settings that include agents such as landlords and tenants, with specific consideration of two issues: split incentives and complexities in decision-making processes. Using two sets of national data, RECS data from 2001 to 2009 and the ACS PUMS 5-year estimate for 2011-2015, this study conducts a logistic regression analysis to investigate whether households with these issues present significant differences in their probabilities of solar energy system adoption with controlling for potential confounding variables.

(3) The third study, titled "Urban Form and Residential Energy Consumption: Exploring the Seasonal Variation of This Relationship in Chicago," investigates how various indicators of urban form, including density, imperviousness, edge contrast, and vegetation, are associated with residential energy consumption; the study explicitly considers seasonal variations. The empirical analysis, which uses a spatial regression model, estimates the effects of urban forms on energy consumption levels in each season as well as on energy consumption ratios between seasons to reveal that each element of urban form has distinct impacts in different contexts.

Moving from a smaller scale to a larger scale, these three studies cover different dimensions of the dynamics of residential energy consumption and energy-related choices. The first study focuses on the dynamics that occur in each household over time, while the second study looks at inter-agent dynamics with explicit consideration of the alignment of incentives and costs in decision-making. The last study pays attention to dynamics at a larger scale, that is, interactions with surroundings, including the built environment and climate. Before presenting these studies, this dissertation first provides a review of the theoretical foundations regarding various aspects of residential energy consumption in order to better explain the dynamic relationships between energy consumption and its determinants. The three studies of the residential energy issues mentioned above follow, and the concluding chapter summarizes the findings and discusses policy implications and suggestions for further studies.

CHAPTER 1

Theoretical Typologies Regarding Residential Energy Consumption

Residential energy consumption, which can be viewed as a result of complex decision making in which human and environmental factors interact, has been extensively examined in many disciplines. The literature is voluminous, encompassing a wide range of theoretical studies (both positive and normative) and applied research from various perspectives. In this chapter, several branches of the literature are reviewed and summarized to comprehensively describe the major theoretical foundations and relevant empirical investigations of residential energy consumption.

Energy Consumption as an Outcome of Economic Decision Making

In economics research, energy use is often characterized as an outcome of deliberate economic decisions made by consumers (or producers) who seek to maximize their utility (or profit) given their own budget constraints. As the price of energy changes over time or across space, the amount of energy consumed is expected to ebb and flow because individual agents tend to economize their bundles of consumable goods and services under their income constraints (Wilson and Dowlatabadi, 2007; Pindyck and Rubinfeld, 2005). Hence, this economic explanation views disposable income and energy price as major determinants of energy consumption because they directly modify the optimal combination of energy and non-energy goods in the utility maximization function.

For example, Houthakker (1951) provides an early study in which residential electricity consumption is described from this type of economic perspective. Using cross-sectional observations in the U.K., he examines how residential energy consumption is influenced by household income, electricity prices, gas (as a substitute) prices, and heavy electrical appliances. According to his statistical analysis, the electricity price is negatively associated with electricity consumption and has an elasticity of -0.61, implying that a 1% price increase reduces consumption by 0.61%. In addition, household income is found to be positively associated with electricity usage, as expected, with an estimated income elasticity of 0.89.

Numerous studies based on different data and methodologies also report similar effects of income and price. Using a generalized least square technique (GLS) with the Consumer Expenditure Interview Survey, which contains rich data regarding households in the U.S., Branch (1993) concludes that the short-run price elasticity is -0.20 and the short-run income elasticity is 0.23. Garbacz (1983) also investigates the effects of price and income on electricity consumption in the U.S. with consideration of the nexus among demand, price, and the appliance stock index. His two-stage least squares model yields a negative price elasticity of -1.40 and a positive income elasticity of 0.41. In other countries, such as Canada (Bernard et al., 1996), Germany (Dennerlein, 1987), Norway (Nesbakken, 1999), Greece (Donatos and Mergos, 1991), Taiwan (Holtedahl and Joutz, 2004), India (Filippini and Pachauri, 2004), and the United Kingdom (Baker et al., 1989), the impacts of price and income show consistent directions. Specifically, price elasticity ranges from -0.76 to -0.21, and income elasticity ranges from 0.17 to 0.53.

Some studies pay attention to the fact that elasticities vary by short- or long-run due to the limited capability of residents to immediately adjust their energy consumption in response to price or income changes. Therefore, it is inevitable that long-term elasticities are greater than short-term elasticities, as reported by a number of studies. In the context of the U.S., Morss and

Small (1989) discovered that the long-run price elasticity is -0.38 (the short-run is -0.23) and that income elasticity is 0.18 (short-run is 0.08). Donatos and Mergos (1990) also report a long-run price elasticity of -0.58 and an income elasticity of 1.50, which are significantly greater than the corresponding short-run elasticities (-0.21 for price and 0.53 for income).

Other studies take slightly different perspectives. For example, some studies pay attention to the role of appliances as substantial determinants of energy consumption because households consume energy through the use of appliances. Parti and Parti (1980) disaggregate total household demand for electricity into various appliance categories to obtain deeper insights into energy consumption behaviors. Although their sample does not include direct observations of appliance-specific energy usage, they employ a conditional demand regression model to estimate the coefficients of detailed demand functions for the disaggregated categories. Using twelve different conditional demand regressions, they find that price elasticity ranges from -0.23 to -1.24, while income elasticity shows a much narrower range: 0.14 to 0.16. Their findings also support the idea that the demand for energy consumption is a function of energy-using appliances and other durables. According to their results, households with a dishwasher use 60 to 140 kW more electricity per month; those with an electric oven use 66 to 87 kW more per month, and those with a freezer use 64 to 92 kW more per month. Dubin and McFadden (1984) also view appliances as durable goods and provide a unified model in which the demand for appliances (durables) and the demand for electricity are jointly determined. In that model, consumers are assumed to consider not only their current financial situation but also their expected future appliance use and future energy prices. Using data for 3,249 households, the authors find that the range of price elasticity is -0.20 to -0.31 and that the range of income elasticity is 0.01 to 0.03, varying by estimation model.

It is interesting that some studies using panel regression models at the disaggregate-level data (at least at a smaller scale than that of the national level) report that income elasticity has a small or insignificant effect on energy consumption. For instance, Garcia-Cerrutti (2000) uses four counties in California, including Los Angeles, Orange, San Diego, and Santa Clara, and discovers that the coefficient for per capita income does not reach statistical significance at the 10% level. Alberini et al. (2011) also report that the effects of income on electricity and gas usage at the dwelling unit level are not significant. At the city level, electricity has a statistically significant association with income, but the magnitude of the coefficient is relatively small (0.02) compared with national-level studies.

Energy Consumption as an Outcome of Psychological-Behavioral Factors

Although studies based on economic perspectives exhibit the evident effect of monetary factors based on the assumption of utility-maximizing agents, a growing number of studies challenge this assumption. Experimental and field evidence highlights the fact that individuals do not always attempt to maximize their utility in the ways explained in traditional economic research (Camerer and Loewenstein, 2011). While economic incentives certainly influence people's behavioral patterns, the impacts of those incentives are contingent and vary across different groups. It is contended that human decision-making, including energy usage, is a highly complex process in which both economic motivations and psychological factors interact (Wilson and Dowlatabadi, 2007).

Insights from psychology are used to address this issue. Attention has been paid to the importance of individuals' personal backgrounds and their perceptions of the external environment in explaining human behaviors. More specifically, researchers have attempted to explain energy consumption with explicit consideration of various norms, attitudes, contextual factors, and feedback processes. Individuals are regarded as agents who seek information and make deliberate decisions based on the expected benefits and costs of the available choices; they are thought to respond not only to monetary incentives but also to other factors that can generate psychological burdens and/or benefits.

According to the theory of planned behavior, individuals' behaviors are mainly guided by three types of beliefs: attitudes towards behaviors, subjective norms, and perceived behavioral control (Ajzen, 1991). These three beliefs determine the psychological benefits and costs that individuals experience. For example, people may have negative feelings when their beliefs conflict with their performed behaviors, while people may feel good when they behave in accordance with their beliefs. A meta-analysis of studies of the theory of planned behavior measures the impact of these beliefs and finds that subjective norms and perceived behavioral control explain 39% of an intention to perform behaviors, while perceived behavioral control accounts for 27% of actual behavioral variances (Armitage and Conner, 2001).

It has been suggested that altruistic and moral motivations are also important in understanding energy consumption and environmental issues. People who have these types of moral norms believe that a behavior that may provide the most benefit to them could also harm other people or the Earth's ecosystems. Therefore, these personal norms of morality can influence individuals to engage in more environmentally responsible behaviors (Stern and Dietz, 1994; Schultz, 2001), such as conserving water and energy in their everyday lives. In addition to norms based on altruistic thinking and morality, there are other norms that yield pro-environmental behaviors. A biocentric-based norm may seem similar to a moral norm, but instead, it views human life as a part of the larger ecosystem (sometimes using unusual terms, such as Mother Earth or Gaia) instead of separating “I” and “others”. Despite this nuanced difference, the practical effect of this norm is similar; that is, individuals who hold biocentric norms are more willing to conserve energy.

While norms are important determinants of energy use, contextual factors also play an important role in determining the amount of energy consumption (Steg and Vlek, 2009). Empirical studies find that some contextual factors, including home ownership, family size, age, and other aspects of the physical and socioeconomic environments, are highly associated with individuals’ engagement in pro-environmental behaviors. For instance, higher income, highly educated, and home-owning households are found to engage in such behaviors more frequently because they are more aware of environmental issues and have a greater ability to undertake energy-efficient investments (Black et al., 1985; Poortinga et al., 2003; Nair et al., 2010). In addition, individual barriers, such as a lack of time, money, or knowledge, have also been found to impact energy consumption behaviors (Karlin, 2014).

Recently, scholars have been attempting to integrate norm-based and context-based theories. This model, referred to as the attitude, behavior, and external conditions (A-B-C) model, posits that environmental behaviors are determined by both norms and contextual factors and that the more influential set of factors (norms or contextual factors) shape the individual’s behavioral pattern (Guagnano et al., 1995). Specifically, an individual’s attitude and surrounding context can range from negative to positive positions (e.g., an individual only performs a certain behavior when coerced vs. without any coercion, and the external condition opposes a certain behavior vs. the external condition is supportive of the behavior). If the barriers to engaging in a pro-environmental behavior are strong, a person is less likely to behave in that way. For instance, home insulation is not strongly affected by normative beliefs; it is more affected by external conditions, such as homeownership (Karlin, 2014). Similarly, regarding recycling behavior, the availability of convenient curbside pick-up (a surrounding context) decreases the explanatory power of an individual's norms (Guagnano et al., 1995). When both types of factors exist, their combination determines a person's behavior: if the combination exceeds a certain threshold, desirable behaviors tend to occur; if not, those behaviors do not occur.

In addition to these factors, Fogg (2009) introduces a third key to human behavior: a trigger—an event that brings attention to target behaviors at appropriate times and acts as a key to behavioral change. Even if a person is beyond the threshold and has a high propensity to perform a particular behavior, that behavior may not be performed without a trigger connecting the person's norms to the action. Triggers can take many forms, such as a campaign slogan, a note on the refrigerator, or feedback. When noticed, these triggers can remind individuals of the importance of certain norms and attitudes and can thus increase people's motivation based on rational or moral standards. Additionally, it is recognized that triggers can simplify complex and vague tasks (e.g., "saving energy") by suggesting desired behaviors and corresponding outcomes (e.g., "If you turn off the water while you brush your teeth, you can save one ton of water each year") and thus help to induce more desirable outcomes.

Bounded Rationality: Behavioral Economics and Energy Consumption

The two theoretical branches explained above, utility maximization and psychological motivation perspectives, do not seem to be easily reconciled. However, there have been efforts to take advantage of both perspectives by incorporating psychological factors into the economic analysis framework. This branch of the discipline, called behavioral economics, attempts to better explain human behaviors based on economic principles and psychological foundations (Camerer et al., 2011).

For instance, some of these studies posit that time discount rates, which are rarely incorporated into conventional utility-based models, are inconsistent (see e.g., Loewenstein and Prelec, 1992; Kirby and Herrnstein, 1995; Frederick et al., 2002). That is, people are more likely to have a high discount rate in the far-distant future, and hence they often prefer short-term gains, even if those gains may result in long-term losses. Further, it is argued that people do not have the same discount rate for all types of consumption; for example, the discount rate for energy-efficient refrigerators may be higher than that for energy-efficient televisions (Gintis, 2000). In addition, people's evaluation system for benefit and loss works differently depending on the given prospective outcomes. People are more risk-averse when they face a high probability of gains and a low probability of losses, but they are more risk-taking when they have a low probability of gains, such as in gambling (Weber and Chapman, 2005). It is also found that people weight losses more heavily relative to gains of equal size. Therefore, when adopting new behaviors, people tend to overvalue potential losses while discounting benefits (Kahneman et al., 1991). These heterogeneous structures, which are involved in estimating the expected benefits and losses caused by people's perceptions, challenge the presumption of conventional economic theory, namely that consumers evaluate the available options rationally to maximize their expected utility.

Further, compared with conventional economic models in which rational actors acquire and analyze all information about possible choices to maximize their utility, the notion of bounded rationality postulates that the cognitive burden of gathering and processing information influences an individual's decision making (see e.g., Simon 1978 and 2000). People tend to use rules-of-thumb or heuristics that simplify given situations in decision-making processes to help reduce their cognitive burdens rather than to maximize utility (Wilson and Dowlatabadi, 2007; Frederiks et al., 2015). For instance, people tend to retain the default settings, or status quo, by which they can reduce cognitive costs in order to make a decision based on all of the available information (Samuelson and Zeckhauser, 1988; Pichert and Katsikopoulos, 2008). Evidence of this status quo is observed across a range of situations, including the residential energy sector. For example, when households are asked about their willingness-to-pay or -accept with regard to the service reliability of the residential electricity supply, a survey design that includes the "status quo" effect brings about a significantly smaller (about three times) willingness-to-pay than a survey design that does not include the status quo effect, and despite the improved service quality, people require compensation merely for changing the default condition (Hartman et al., 1991).

The theories of behavioral economics have been applied to various sectors. In particular, the concept of loss aversion can be applied such that energy information is presented to audiences as loss prevention rather than gain creation (e.g., "You are losing $5 a month by not turning off your lights"). Regarding time inconsistency (people tend to prefer immediate gains), governments have implemented policies that repackage costs so that the benefits appear first. In relation to the heuristics through which people seek to reduce their cognitive load, the number of energy-saving tips or policies can be limited, such as by presenting "five tips to save the earth" instead of more than one dozen home weatherization options (Houde and Todd, 2011). On the other hand, bounded rationality can also impede improvements to energy conservation and efficiency. For instance, because they prefer the status quo, discounting future gains, and over-reacting to potential losses, people may hesitate to adopt energy-efficient appliances and systems, which provide long-term benefits while requiring larger and immediate investments than less energy-efficient appliances.

Energy Consumption and the Human Body as a Thermal Recipient

Aside from the economic and psychological perspectives, a human being can be viewed as a physical entity that interacts with the environment, and energy consumption can be understood as part of the way in which human body systems work and adapt to new environments. This perspective assumes that the human is a passive and static thermal recipient and a physical being that maintains a constant temperature regardless of external circumstances. That is, an occupant of a building is regarded as a "physical entity occupying space, manipulating devices…a physical system in a physical world" (Lutzenhiser, 1992, p. 50). According to this perspective, energy consumption patterns can be formed and predicted using a combination of physical settings (e.g., the insulation value of clothing) and non-thermal settings (e.g., gender, age, and culture) (Brager 1998). Thus, if a greater thermal imbalance between the human body and its surrounding environments exists, an increase in energy consumption is predicted.

While some researchers have questioned whether this simple cause-and-effect approach can accurately describe real-world dynamics and complexity, others have contended that a new model, the so-called thermal adaptation model, is capable of overcoming the simplicity of the thermal comfort model. The thermal adaptation model exists in between the social sciences and physics, presenting the notion that people interact with their environments by creating their thermal preferences or modifying their expectations. The main principle of the adaptive model is as follows: "If a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort" (Nicol and Humphreys, 2002, p. 564). Unlike genetic adaptation, this type of adaption changes an individual's settings for their "physiological thermoregulation system" in the short term, within days or weeks, in response to constant thermal stimuli. This model implies that energy use behaviors in buildings can be changed as a person's physio-psychological characteristics become accustomed to his or her external environment (De Dear and Brager, 1998; 2001).

The Complexity of Energy Consumption

The literature shows that energy consumption is an extremely complicated process shaped by economic conditions, personal norms, psychological attributes, physical environments, and other factors. Many studies from a wide range of disciplines have been devoted to revealing different aspects of energy consumption. Economic perspectives note that energy consumption is determined by utility-maximizing individuals, while psychological perspectives emphasize the importance of internal human factors and the surrounding socio-psychological contexts. Human beings can also be regarded as thermal entities that interact with external thermal conditions.

Although each branch of the literature provides a useful lens through which energy consumption behaviors can be examined, our current knowledge is still far from complete. This limited knowledge base calls for a multidisciplinary approach to understanding the complexity and dynamics of energy consumption. Through the following three studies, this dissertation seeks to achieve a more complete understanding of the nature of energy use, with careful consideration of various factors operating at multiple scales.

CHAPTER 2

The Micro-level Dynamics of Residential Electricity Consumption

Introduction

Determinants of residential energy usage have long been explored and examined in many studies and from various perspectives. Some scholars view residential energy usage as mostly an outcome of physical elements (Quan et al., 2014; Rode et al. 2014); these scholars suggest that appropriate reformation of the surrounding environment, such as building design or urban form, is a strategy for potential energy savings. On the other hand, other scholars place more emphasis on norms and behavioral attributes (Ajzen, 1991; Schultz, 2001), arguing that human factors are another key to making meaningful changes in energy consumption patterns and that understanding how people behave in specific situations is essential.

Given these competing views, it is generally accepted by many scholars that residential energy consumption is determined through a mechanism in which both human and environmental factors come into play. Specifically, they view energy consumption patterns as a result of the reciprocal interactions between the surrounding physical environment and human socio-economic/behavioral factors, and a change in one factor can have direct impacts on final energy consumption as well as indirect effects on other connected factors (Wilson and Dowlatabadi, 2007; Steemers and Yun, 2009). This comprehensive perspective contributes to expanding our knowledge base about the complex nature of residential energy consumption, and it also offers a greater ability to estimate the overall effect of changes in multiple determinants on the amount of energy consumption.

Additionally, there is growing interest in the dynamic aspects of energy consumption. This perspective posits that the interactive relationship between humans and the environment can be differently shaped by various settings. For instance, the adaptive thermal comfort theory argues that the human body's response to external thermal conditions evolves over time as people are increasingly exposed to the environment and become accustomed to it (Fuller and Bulkeley, 2013). Additionally, given the same dwelling unit, significant differences are found between residents who have recently moved in and residents who have lived there for a longer period (Sonderegger, 1978). These findings suggest that residential energy consumption is not a static system but rather a dynamic system in which various determinants construct complicated linkages and relationships evolve over time.

As Dieleman et al. (2000) present, the U.S. has different mobility patterns; some areas have active housing markets with large amounts of new construction, while other cities have stable housing markets with fewer housing relocations. Given the dynamics of energy consumption, areas with different mobility patterns exhibit distinct energy consumption mechanisms in their residential buildings; thus, understanding this side of energy consumption is very important to building successful energy policies. However, there has been a lack of interest in this topic, creating a blind spot on this dynamic in the literature. To fill this gap, this study investigates how the relocation of households brings about different energy consumption patterns and how those patterns change over time. The next section reviews studies on residential energy consumption that adopt various perspectives and approaches.

Previous Studies on Residential Energy Consumption

Previous empirical studies concerning residential energy consumption can be categorized into two major groups in terms of their units of analysis: aggregate-level research using national or regional data and individual- or household-based investigations. There are many aggregate-level studies investigating the influences of macroeconomic factors (e.g., energy price, gross domestic product, and inflation) and/or analyzing the historical trends of residential energy consumption (e.g., Donatos and Mergos, 1991; Ang et al, 1992; Holtedahl and Joutz, 2004; Narayan and Smyth, 2005, 2007; De Vita et al., 2006; Halicioglu, 2007; Ziramba, 2008; Arisoy and Ozturk, 2014; Salisu and Ayinde, 2016). However, although these approaches can significantly reduce data requirements, their reliance on aggregate-level data can be a shortcoming. In other words, the neglect of detailed building and household characteristics is likely to result in overlooking the importance of microlevel factors in determining the amount of energy use and in achieving potential reductions in energy consumption, as Swan and Ugursal (2009) noted. Because this study examines variations in household-level energy use, this literature review excludes those aggregated studies and focuses on disaggregated studies.

Studies conducted at a disaggregated level generally consider various attributes of individual households, such as household demographics and economic status, appliance ownership, and housing unit characteristics, despite the significant time and effort required to produce such rich disaggregate-level datasets. However, the virtue of this approach is its ability to explain micro-level variations in energy consumption. As there are numerous types of data, disaggregated studies also use various statistical methods. Among these methods, linear regression is the most widely used due to both its simplicity and the efficiency of its predictive power compared to the computational tasks required (Fumo and Biswas, 2015). For example, Douthitt (1989), using data from an in-person survey of 3,640 Canadian households between 1981 and 1982, constructed a heating fuel consumption model for a residential space. He used an ordinary least squares (OLS) regression for each type of energy consumption to understand how residential energy use is determined by substitute fuel prices; total fuel expenditures; and the vector of building structure attributes, thermal conditions, climate, and occupant characteristics. He discovered that the residential uses of space-heating fuel in Canada responded to energy price changes; more specifically, in the long run, residents exhibited a negative elasticity of energy demands for fuel prices.

In the context of the U.S., Elsawaf et al. (2012) use a multiple regression model to evaluate the efficiency of using heat pumps for space heating in eastern North Carolina. Their results show that housing unit size, building storage, and number of households are positively associated with residential energy usage at the 5% level of significance, while the presence of a heat pump is found to reduce energy consumption. Min et al. (2010) also employ a multivariate regression model using the 2005 RECS with a sample of 4,382 households in the U.S. To estimate residential energy consumption, they use a two-step analysis. That is, they first estimate the influences of socio-economic determinants on appliance ownership, heating, and cooling energy usage. These estimated coefficients are applied to census data at the zip code level to calculate the aggregated energy consumption of each zip code area. In their regression model, the price of electricity is shown to have a negative effect on electricity consumption, while heating degree days (HDD) and cooling degree days (CDD)[1], household size, household income, and the number of heated rooms are positively associated with electricity consumption. In addition to the studies mentioned, many other disaggregate-level studies using regression models have examined the linear relationship between socio-economic/demographic determinants and residential energy consumption (Dubin and McFadden 1984; Pachauri, 2004; Yoo et al., 2007; Kaza, 2010; Brounen et al., 2012; Chen et al., 2013; Schleich et al., 2013; Gans et al., 2013; Villareal et al., 2016; Belaïd, 2016).

Researchers have paid attention to the structural equation model that reveals not only the direct effects of determinants on energy consumption but also the indirect effects by considering the reciprocal connections among these variables, with the goal of better addressing the complexity of residential energy consumption. For example, using the 2001 RECS, Steemers and Yun (2009) estimate the structural effects of climate, housing unit characteristics, and the socio-economic status of households on heating and cooling energy consumption in a house. They discovered that the standardized total (sum of direct and indirect) effect of climate on residential energy use is the highest, followed by heating type (the main heating type is electricity) and heated floor area. However, the characteristics related to occupants, including annual income, age of household head, and the number of household members, have relatively lower impacts. A similar pattern is found in the case of cooling energy consumption. In the estimation, it is

[1] Heating/cooling degree days are calculated by taking the difference between the average of (i) a day's high and low temperature and (ii) the base temperature (65°F). For instance, if a day's average temperature is 55°F, the heating degree day is 10 (65-55), whereas if a day's average temperature is 75°F, the cooling degree day is 10. Annual or monthly heating/cooling degree days are summations of each day's amount.

interesting that some variables have only an indirect effect. The number of household members is positively associated with heating energy consumption in a major way through floor area, number of windows, and number of heated rooms. Number of windows has a positive relationship with number of cooled rooms, and thus, it is positively associated with cooling energy consumption.

Kelly (2011) also employs a structural equation model to explain residential energy consumption in the U.K. with an emphasis on the reciprocal relationship between housing energy efficiency and energy consumption. Using the English House Condition Survey and the Fuel and Energy Survey of 1996, which provide 2,531 unique cases, the author reveals that a housing unit with poor energy efficiency can consume more energy. However, higher residential energy use can also lead to investing in energy-efficient improvements, which suggests the existence of the rebound effect in dwelling units. In addition to the main findings, the results of the analysis show that household size, floor area, and household income have sizable influences on household energy expenditure; the standardized total effects of these factors were 0.42, 0.26, and 0.24, respectively.

It is worth noting that other methodologies also exist, such as conditional demand analysis (e.g., Parti and Parti 1980, Aigner et al., 1984) and neural network models (e.g., Kialashaki et al. 2013; Aydinalp et al., 2004). Parti and Parti (1980) estimate monthly electricity demands by disaggregating the total demand into each appliance based on the conditions of the housing unit. For example, in April, the estimated coefficients for air conditioning in multifamily units with central air conditioning is 9.8, while the value for multifamily units with window air conditioners is -29.0, the value for a single-family unit with central air conditioning is -19.5, and the value for a single-family unit with a window air conditioner is -72.9. The advantage of the conditional demand analysis is its good predictive power. However, it also has a disadvantage in considering socio-economic factors and energy-saving scenarios. By contrast, neural network models have advantages in flexibility that allow them to reflect microlevel factors (i.e., socio-economic and demographic characteristics) with reasonably high predictive power. Moreover, this type of model can efficiently handle multicollinearity and non-linearity. However, neural network models lack transparency due to their very nature; in other words, this model cannot show the specific impacts of each variable.

Despite the ability of these various approaches to address the complicated nexus of socio-economic and physical variables and energy consumption in a house, they commonly overlook the issue of how energy consumption patterns vary in a housing unit over time. Recently, Alberini et al. (2011) addressed this issue by taking advantage of household-level panel data. Specifically, using AHS data from 1997 to 2007, they conducted a static panel model with fixed effects for each housing unit and a partial adjustment model that considers both the long-run and short-run equilibrium demands of energy. According to their results, the price elasticity ranges from -0.667 to -0.692 (based on dwelling units) in static models. In the dynamic model, it ranges from -0.736 to -0.743 in the short run, and long-term elasticity ranges from -0.814 to -0.820. In addition, it is notable that income elasticity in a dwelling-unit-based fixed effect model is quite a bit smaller (0.01 ~ 0.02 or not significant) than is income elasticity in the literature, and it is even lower than in city-level panel analysis. This difference implies that the influences of socio-economic determinants, such as income, on energy use can differ if those determinants are observed within each housing unit.

In sum, the literature on residential energy consumption has attempted to identify the diverse effects of energy consumption determinants by using various statistical approaches at the disaggregated level. As shown in the previous chapter, however, some disciplines that are based on human behavioral perspectives do not view residential energy consumption as a result of a mathematical function that is composed of various factors but rather as an outcome of dynamic relationships among personal attitudes, norms, and contexts that can stimulate certain behaviors; the literature reviewed above overlooks this dynamic aspect of residential energy consumption.

To the best of my knowledge, there is only one empirical study that focuses on this dynamic. Using data from Twin Rivers, California over two winters (1971-1972 and 1973-1974), Sonderegger (1978) compares gas consumption between “stayers”, who have been living in the same house, and “movers”, who moved into a new house during 1972-1973, to examine whether households have significant impacts on energy consumption in homes after controlling for the influences of dwelling units. According to his hypothesis, compared to stayers, movers should reveal different energy consumption patterns in the second winter (1973-1974) due to household changes. As expected, the results provide clear evidence that the dwelling units associated with the mover group show a different gas consumption pattern between the two winters. Specifically, they tend to consume more energy in the second winter than the previous winter and have a higher variance in energy consumption than do the dwelling units occupied by stayers. Although the Twin Rivers study can be criticized for not controlling out confounding factors, including household income and composition, which makes the data on the precise impacts of moving to new homes less reliable, the results still suggest some clues about the dynamics of residential energy consumption.

Related to this, Fogg (2009) provides an important theoretical insight based on the so-called trigger, which can prompt people to remember certain norms, pay attention to specific behaviors, and ultimately change their behaviors. Triggers can take different forms, from slogans to feedback from other family members. In the context of Sonderegger's study, moving to a new home may serve as a strong trigger. That is, being in a new environment draws people's attention to energy consumption and makes them more aware of energy-efficient appliances. However, there is a lack of scholarly attention to this topic.

To fill this gap, this study attempts to investigate the dynamics of residential energy consumption in individual households and explicitly considers the household's move and period of residence. The next section describes the details of the empirical analysis, including the analytic framework, model data, and variables used in examining these dynamics.

Analytic Framework, Model, Variable, and Data

Analytic framework and model. It is difficult to investigate the differences between stayers and movers with data from a single time point. Because there are numerous confounding variables, some of which are even unobservable, a cross-sectional study would not enable us to determine exactly how the period of residence comes into play. However, this problem can be effectively addressed through panel models, which employ the fixed effects of each unit of analysis and provide more power to control unobserved effects in a systematic and efficient manner.

Similar to cross-sectional models, panel models include independent variables that are observable at each time point. However, unobserved effects that influence residential energy consumption over time still exist. To capture these effects, a panel model, particularly the fixed-effect model, adds individual-specific fixed-effect variables. In this way, the influences of unobserved factors, which are assumed to be consistent over time (e.g., households' energy use patterns are consistent during the study period), are reflected in the fixed-effect dummy variables of the panel model. Therefore, this analytical method is able to successfully and efficiently address unobserved variable problems. Additionally, this advantage of panel models better serves the purpose of this study in terms of the possibility of inter-temporal comparison of housing units.

However, a downside of the panel model is the difficulty of data collection, especially at more disaggregated levels. While there are some household-level surveys, it is unfortunate that they all use random sampling methods, making it impossible to construct a longitudinal dataset. Taking a novel approach to solving this problem, this study focuses on housing units instead of households because housing units are immobile and are hence likely to be repeatedly surveyed over time. Fortunately, among the available data sources, the AHS meets these criteria and enables panel analysis because a part of its sample pool (housing units) survives over time. By exploiting this advantage of the AHS, this study uses a panel analysis based on housing units, as shown in Figure 2.1.

It should be noted that Alberini et al. (2011) used this same housing panel approach and the same data source in their analysis of price elasticity. Essentially, this study follows their approach, but with the following differences:

(1) Alberini et al. restrict their sample to single-family homes and duplexes, but this study also includes multifamily dwelling units.

(2) Alberini et al. use AHS national data from 1997 to 2007 and AHS metro data from 2003 to 2007, while this study takes advantage of more recent and longer period observations, that is, AHS national data from 2001 to 2013.

(3) Alberini et al. use an unbalanced panel ranging from 4 to 12 years in length (i.e., 2 to 6 timepoints); however, this study uses a balanced panel with seven timepoints over 13 years (7 surveys).

(4) Alberini et al. conduct both static and dynamic panel models and focus on comparing short-term and long-term elasticity; however, this study only examines a static model and focuses on comparing movers and stayers.

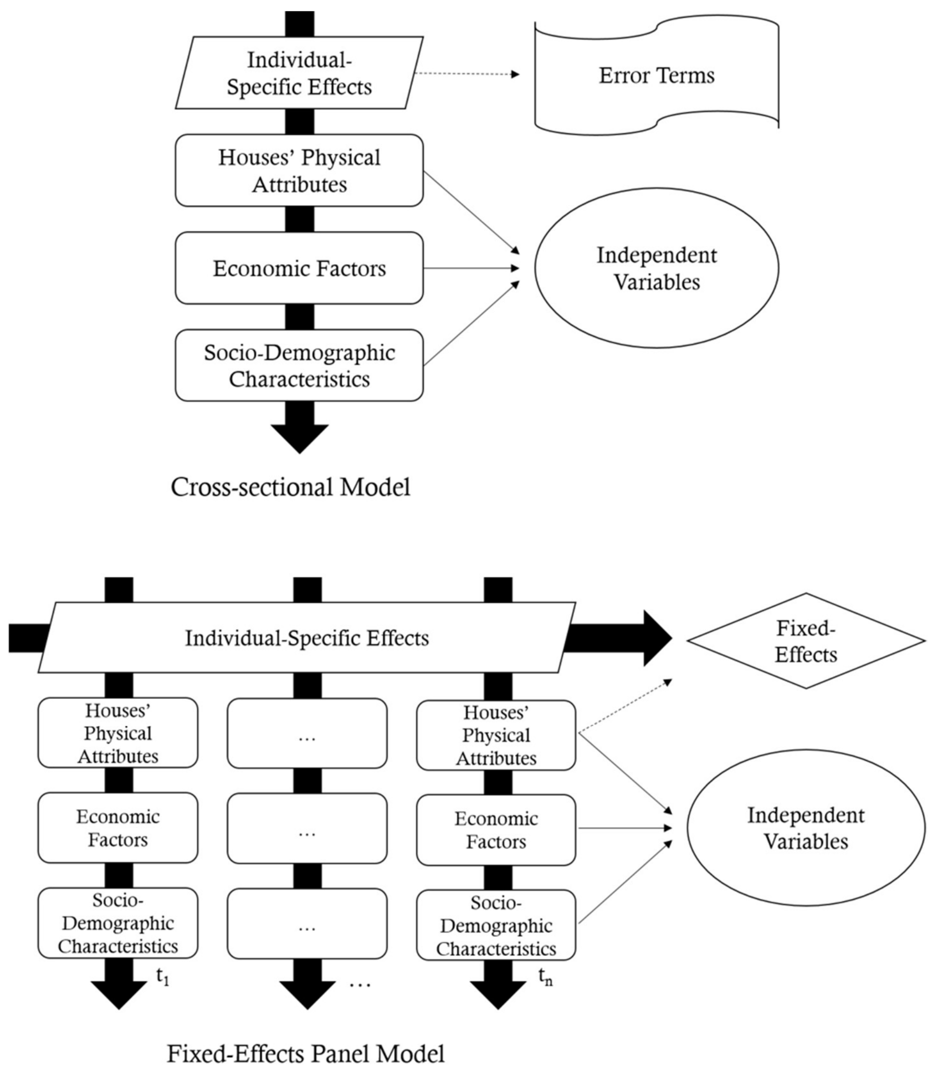


Figure 2.1 Comparison of the Cross-sectional Model and the Fixed-effect Panel Model

Variables and data. As mentioned above, this study employs AHS data from 2001 to 2013. The surveys are conducted biennially with sample sizes of over 60,000 households each year, and they collect information on a wide range of housing and household characteristics, including total household income, the age of the head of the household, the educational status of the head of the household, the number of residents, tenure type, building type, building age, floor area, appliance ownership and attributes, and average monthly energy costs.

It is important to note that this study adopts the following sample selection process. First, all data records from non-metro areas (*SMSA*=9999) are excluded due to the impossibility of employing state-level data, including energy price and climate. Out of 611,948 observations from seven timepoints, this process eliminates 265,192 non-metro housing units. Next, 84,345 observations are further removed due to missing data problems in some key variables, such as housing unit size[2], electricity consumption, and housing unit type. To create a balanced panel, housing units that are observed throughout the whole study period (seven timepoints) are then selected. This process drops a significant number of observations, and consequently the sample size becomes 32,382 with 4,626 unique housing units.

In terms of the formulation, a simple equation of this panel model is as follows:

$$\ln(ELEC_{it}) = \beta_0 \cdot RESID_{it} + \beta_1 \cdot X_{it} + \gamma_i \cdot HU_i + \gamma_t \cdot YR_t + \varepsilon_{it}$$

[2] If a housing unit size is missed in between two identical values, it is assumed to have the same value (e.g. when 2003 = 1,200 square-feet, 2005 = not available, and 2007 = 1,200 square-feet, 2005 becomes 1,200 square-feet).

where $RESID_{it}$ is the household's resident period, measured by employing a set of dummy or continuous variables; X_{it} is a vector of other explanatory variables, including external conditions, household characteristics, housing unit characteristics, and household appliance ownership status. To capture the fixed effects, dummies for individual housing unit, HU_i, and survey year, YR_t, are added to the model. γ_i and γ_t are groups of coefficients for the fixed-effect variable for housing units and the fixed-effect variable for survey years, respectively. Lastly, ε_{it} is the error term, assumed to be uncorrelated with the explanatory variables and individual- and time-specific effects.

Specifically, this fixed-effect panel regression model estimates the effect of each variable's variance around the mean for each housing unit, and the combined set of these average effects of each housing unit is captured as a "fixed" constant. While the fixed-effect implies the constant effect of each cross-sectional unit across time (HU_i), a similar explanation can be applied to longitudinal time points across housing units (YR_t). In sum, the fixed-effect model employed in this study removes the average effects of both each housing unit (e.g., locational characteristics or physical conditions that are omitted from the model) and each timepoint (e.g., recession or economic prosperity).

The dependent variable is electricity consumption (*ELEC*), which is calculated by dividing the average monthly total electricity cost by the average electricity price in the area, which is adjusted to 2013 dollars. On average, electricity consumption per household per month is 940 kWh, and the standard deviation is 648 kWh. For ease of calculating elasticity, this dependent variable takes a log form.

To investigate the temporal dynamics among households, this study measures the residence period of households in the following two ways. First, it employs a set of dummy variables indicating how long a household has lived in the current dwelling unit. There are four dummy variables (*RESID12*, *RESID34*, *RESID56*, *RESID78*), and each one indicates the period of residence, grouped stepwise by a couple of years to match the period of the biannual AHS surveys[3]. For instance, *RESID12* indicates households who have been living in the home for two years or less, and *RESID78* refers to households who have been living in the home for seven or eight years. Theoretically, 42 (the maximum value of the residence period is 84) dummy variables could exist, but practically, such an excessive number is not desirable. Therefore the present study instead uses a continuous variable that represents the residence period (*RESIDP*), as an alternative metric, in order to examine the overall pattern between energy consumption and residence period.

Control variables can be categorized into several groups. In the first group of variables, this study incorporates those variables related to the external conditions. *PRICE* is the average annual electricity price (logged) in each state and each year, as compiled from the Electric Power Monthly Reports provided by the U.S. Energy Information Administration (EIA). Although consideration of a flexible energy pricing tariff is important to examine the price effects, the average prices are also important (Shin, 1985), and delving into the detailed impacts of energy prices may be a less efficient approach for the focus of this study. To capture climate effects, this study employs two metrics, *HDD* and *CDD*, which refer to the sums of the differences between the average daily temperature and the base temperature (16.5°C or 65°F in this study) for each

[3] Practically, this grouping can increase the degrees of freedom in the statistical analysis.

state and each year. For example, *HDD* for an area with average daily temperatures of 60, 61, 62, 59, 55, 62 and 60°F over a seven-day period is 36 for the week (5+4+3+6+10+3). For this calculation, data are collected from the Degree Days Statistics published by the Climate Prediction Center of the National Weather Service. Higher *HDD* and *CDD* imply a greater amount of residential energy consumption because people tend to maintain a certain thermal setting in their homes, and if temperatures are higher or lower than that setting, then residents use heating/cooling appliances and consume more energy. In the analysis, these variables are divided by 1,000 for the purpose of legibility.

The second variable group is household characteristics, covering socioeconomic and demographic factors. As in many previous studies investigating income elasticity, this study considers total household income (*HHINC*), measured as the sum of all household members' annual incomes. To reduce skewness and make checking elasticity easier, the variable is logged to improve normality. Because more disposable income can lead to more energy consumption, this study expects a positive relationship between income and energy expenditure (Parti and Parti, 1980; Dubin and McFadden, 1984). Household size (*HHSIZE*) is another important determinant of energy consumption. As the number of people living in homes increases, the household is likely to use more lighting and heating/cooling appliances; thus, energy consumption increases. However, this relationship may not be linear. That is, keeping other conditions (e.g., housing unit size) equal, an increasing rate of energy consumption can diminish as the size of a household increases. Therefore, the household size variable is used in a log form, similar to the variables mentioned above.

To control for the effects of other household characteristics, this study also considers each head of household's age and educational attainment level using three dummy variables, *ELDER, YOUNG,* and *HIGHEDU*, which indicate that the household has at least one household member older than 60 (*ELDER* = 1), at least one household member younger than 6 (*YOUNG* = 1), and at least a bachelor's degree (*HIGHEDU* = 1). Previous research has suggested that elderly populations tend to use more energy, but no clear consensus exists regarding the effect of education on energy consumption. Homeownership (*OWNER*) is also considered to reflect the difference between owners (*OWNER* = 1) and renters. Because most homeowners pay their utility fees, they may be more incentivized to reduce their energy consumption.

The third group of variables is housing unit characteristics. This group includes housing type, housing unit size, number of rooms, building age, and main heating fuel. There are two dummy variables for housing type, single-family (*SINGLE*)[4], duplex (*DUPLEX*) and apartment (*APARTMENT*). Both are expected to show a negative association with energy consumption because these types of housing are less susceptible to the exterior climate than is the reference type (i.e., single-family home) due to the smaller area of exposed walls, windows, and roof. Housing size is measured in square feet (*UNITSF*—logged to improve normality). Because increased living space usually leads to more heating, cooling, and lighting demands, the expected effect is positive. In a similar vein, the number of rooms (*ROOMS*) is also included. Age of building (*BLDAGE*) indicates the difference between the survey year and the year the building was constructed. While it is usually believed that old homes are less energy efficient than newer ones, they also have a greater chance of renovation, and no clear expectation is attributed to the

[4] *SINGLE* is the reference group.

building age variable. Additionally, a dummy variable showing whether a house's main heating fuel is electricity (*HELEC* = 1) is included to reflect differences in electricity usage by main heating fuel type.

The last group of variables is the ownership of various appliances. This variable is used to reflect the impact of certain appliances on an individual household's energy use. More specifically, consideration is given to a range of appliances that can reflect variations in households' lifestyles, including the oven/stove (*COOK*), refrigerator (*REFR*), dishwasher (*DISH*), washing machine (*WASH*), room air conditioner (*AIR*), and system air conditioner (*AIRSYS*)[5]. Each of these variables is coded with a binary manner (i.e., 1 is assigned to the households owning at least one unit of the appliance, and 0 is assigned when no such appliance is owned). The descriptive statistics of these variables are presented in Table 2.1 along with the variables' descriptions and sources.

Before reporting the results, it should be noted that the coefficients derived from the fixed-effect panel data regression need to be carefully interpreted. Because an average effect of each cross-section over time is absorbed into the fixed effects, the magnitudes of the coefficients indicate "impacts of a difference from the average" (Gujarati, 2003). For instance, if an average *HDD* over seven timepoints is 2,000 and the coefficient for *HDD* is 0.05, it means that the dependent variable increases by 5 when the *HDD* is 2,100 and decreases by 5 when the *HDD* is 1,900. For this reason, some housing unit (*DUPLEX*, *APARTMENT*, *BLDAGE*) and home

[5] *DRYER* is removed because all samples have dryers; therefore, no variance exists.

appliance (*COOK*, *REFR*) variables are removed because they create multicollinearity issues with cross-sectional or time-series dummies. However, all six variables are included in the pooled model estimation presented in the next section.

Table 2.1 Descriptive Statistics of Panel Dataset based on Housing Unit

	Mean	St. Dev.	Minimum	Maximum	Data Source
ELEC (kWh)	940	648	6.17	7145	AHS[a], EPMR[b]
RESID12	0.11	0.31	0	1	AHS
RESID34	0.09	0.28	0	1	AHS
RESID56	0.07	0.26	0	1	AHS
RESID78	0.07	0.26	0	1	AHS
RESIDP	15.95	13.88	0	84	AHS
HHINC	95351	105112	1	4569968	AHS
PRICE (cents/kWh)	13.06	3.07	7.37	36.98	EPMR
HDD	4148	2107	0	9162	DDS[c]
CDD	1367	976	223	4754	DDS
PER	2.74	1.50	1	18	AHS
OWNER	0.82	0.39	0	1	AHS
YOUNG	0.15	0.36	0	1	AHS
ELDER	0.38	0.49	0	1	AHS
HIGHEDU	0.75	0.43	0	1	AHS
UNITSF	1955	1627	99	24870	AHS
ROOMS	6.32	1.85	1	21	AHS
HELEC	0.22	0.41	0	1	AHS
BLDAGE	49.12	21.54	0	94	AHS
SINGLE	0.81	0.39	0	1	AHS
DUPLEX	0.04	0.19	0	1	AHS
APARTMENT	0.14	0.35	0	1	AHS
COOK	1.00	0.05	0	1	AHS
REFR	1.00	0.03	0	1	AHS
DISH	0.71	0.45	0	1	AHS
DRY	0.86	0.34	0	1	AHS
WASH	0.89	0.31	0	1	AHS
AIR	0.25	0.43	0	1	AHS
AIRSYS	0.66	0.47	0	1	AHS

[a] American Housing Survey 2001–2013
[b] Energy Price Monthly Report 2001–2013
[c] Degree Days Statistics 2001–2013

Results

Fixed-effect model using the whole sample. The results in Table 2.2 present the different impacts of the period of residence (i.e., *RESID12 ~ RESID78*) on electricity consumption in all observed housing units. Columns #1 to #4 employ dummy variables, which are added incrementally from a recent move (within 2 years) to a move that occurred longer ago (up to 8 years). A pattern is found in that recent movers (*RESID12*) use less electricity but tend to increase their energy use as time passes. Specifically, *RESID12* has negative coefficients – ranging from -0.022 to -0.030 – at the 5% significance level across the models and is always the smallest value among the mover status dummy variables. *RESID34* also has negative coefficients at the 5% significance level, except in column #3, and the values of coefficient range from -0.019 to -0.027, showing the second-smallest coefficient value following *RESID12*. *RESID56*, which indicates households who have resided in their homes for over five years, does not show any statistical significance, and a coefficient for *RESID 78* shows that households who have been living in their homes over seven years tend to consume greater amounts of electricity. This pattern is visualized in Figure 2.2.

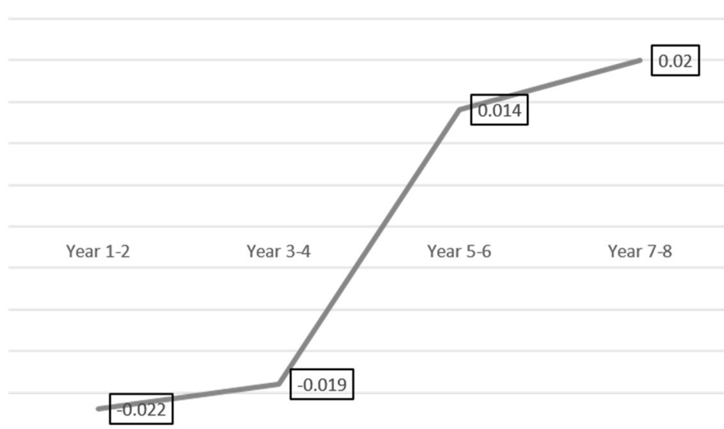


Figure 2.2 Changes in Energy Consumption by Period of Residence (Dummy Variable)

Table 2.2 Effects on Electricity Consumption by Different Residence Periods

	(1)	(2)	(3)	(4)	(5)	(6)
RESID12	-0.022 **	-0.030 ***	-0.028 ***	-0.022 **		
RESID34		-0.027 ***	-0.025 **	-0.019 *		
RESID56			0.008	0.014		
RESID 78				0.020 *		
RESIDP					0.001	
log(RESIDP [a])						0.039 ***
log(HHINC)	0.004	0.004	0.004	0.004	0.005	0.005
log(PRICE)	-0.453 ***	-0.453 ***	-0.453 ***	-0.453 ***	-0.453 ***	-0.449 ***
HDD	0.060 ***	0.060 ***	0.059 ***	0.059 ***	0.060 ***	0.060 ***
CDD	0.077 ***	0.077 ***	0.076 ***	0.077 ***	0.077 ***	0.075 ***
log(PER)	0.205 ***	0.205 ***	0.205 ***	0.204 ***	0.206 ***	0.207 ***
OWNER	-0.025	-0.026 *	-0.027 *	-0.027 *	-0.025	-0.047 ***
YOUNG	-0.058 ***	-0.056 ***	-0.057 ***	-0.058 ***	-0.059 ***	-0.052 ***
ELDER	-0.0002	-0.0016	-0.0012	-0.0002	-0.0024	-0.0159 *
HIGHEDU	-0.010	-0.009	-0.009	-0.009	-0.009	-0.007
log(UNITSF)	0.067 ***	0.066 ***	0.066 ***	0.066 ***	0.067 ***	0.065 ***
ROOMS	0.020 ***	0.020 ***	0.020 ***	0.020 ***	0.020 ***	0.020 ***
HELEC	0.119 ***	0.119 ***	0.119 ***	0.120 ***	0.119 ***	0.119 ***
COOK	0.056	0.056	0.057	0.056	0.056	0.057
REFR	-0.048	-0.047	-0.047	-0.047	-0.048	-0.045
DISH	0.055 ***	0.055 ***	0.055 ***	0.054 ***	0.056 ***	0.056 ***
WASH	0.093 ***	0.093 ***	0.093 ***	0.093 ***	0.093 ***	0.087 ***
AIR	0.030 ***	0.030 ***	0.030 ***	0.030 ***	0.030 ***	0.029 ***
AIRSYS	0.054 ***	0.055 ***	0.054 ***	0.054 ***	0.054 ***	0.056 ***
Obs.	32,382[b]	32,382	32,382	32,382	32,382	32,382
Adj. R^2	0.670	0.670	0.670	0.670	0.670	0.671

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level
[a] Added by 1 to avoid log(0) error [b] 4,626 housing units × 7 years

In columns #5 and #6, a continuous variable of the residence period (*RESIDP*) is used instead of the dummy variables. It is important to note that no significant linear relationship is detected between electricity consumption and *RESIDP*. However, when a logged form of *RESIDP*[6] is used, it is found to be positively associated with electricity consumption at the 1% significance level. Overall, the outcomes in Table 2.2 suggest that recently relocated households are likely to consume less electricity, but as those households reside in a dwelling unit longer and become accustomed to the living environment, they increase their electricity consumption. This is an interesting finding about micro-level dynamics. However, it should be stressed that the results presented in columns #5 and #6 suggest that this increase ends at some point, perhaps when households are fully adjusted to their new dwelling units and their energy consumption is saturated.

Regarding income elasticity, household income turns out to have no significant impacts when analyzed through panel data analysis. This finding is roughly consistent with the results of Alberini et al. (2011), who reported a much smaller influence of income on residential energy use than did other studies using cross-sectional models. The result should not be interpreted as showing that household income does not matter. Rather, it suggests that residents in the same physical environment (house) are less likely to change their energy use patterns dramatically in response to changes in their income. For instance, when households have a significantly higher income level, they are unlikely to consume excessive energy for space heating and cooling under

[6] To avoid log(0) error, the value is shifted up by 1.

similar housing characteristics because excessive heating and cooling instead harms residents' comfort and utility. However, they may decide to change their physical environment; for instance, they may purchase additional appliances, which in turn would yield greater energy consumption, or move into bigger homes, which cannot be fully reflected in a housing-unit-based analysis. This result is in line with the findings of Estiri (2015), which shows the relative importance of building characteristics compared to socio-economic characteristics in determining residential energy consumption. Meanwhile, price elasticity is negative, with a range of -0.449 ~ -0.453, meaning that households reduce their energy use in response to increases in price. The magnitude of elasticity is also consistent with previous studies, such as Nesbakken (1999) (-0.33 to -0.66) and Filippini and Pachauri (2004) (-0.29 to -0.51). Of the other external factors, climate variables also have the expected impact. In detail, *HDD* and *CDD* are positively associated with electricity consumption, as expected, but *CDD* (0.075) has a greater effect than *HDD* (0.060) because cooling appliances generally use electricity, while space heating often uses alternative energy sources, such as gas, wood, and coal.

For household characteristics, the logged form of the number of household members shows a positive linkage to electricity consumption. However, homeownership has a negative association with the dependent variable, although its significance level is not very stable across the models. This finding means that renter-occupied dwelling units consume more electricity, which is seemingly due to the split incentives among landlords and tenants, a topic that is discussed in the next chapter. The presence of a young child under 6 is negatively associated with electricity consumption, while both the presence of elderly family members (aged 60 or over) and the presence of a household member with a bachelor's degree or above show no significance.

In regard to housing unit attributes, *log(HHSIZE)* (0.065-0.067), *ROOMS* (0.020), and *HELEC* (0.119-0.120) are all significant and positively associated with electricity consumption; these findings are similar to the results of Alberini et al. (2011) in terms of their directions and magnitudes. More specifically, using the fixed-effect model based on dwelling units, they report that the coefficient for logged housing unit size is 0.052, the coefficient for number of rooms is 0.01, and the coefficient for the electric heater dummy is 0.123. Considering the differences in the data and in the variable set, the results of this study fall in a reasonable range. In fixed-effect models, the variance of the dwelling unit is relatively small because physical changes to the dwelling unit, such as retrofitting or expansion, are extremely rare. However, these results imply that small changes still have significant impacts on electricity consumption. Additionally, appliances all have positive and significant coefficients except *COOK* and *REFR*. The reason for the insignificance of these appliances is a lack of variance among the sample; in other words, almost all households have a cooking range (99.7%) and a refrigerator (99.9%).

This study further tests various interaction variables to examine how the mover effect differs according to the socio-economic status of the residents or the physical characteristics of the housing units. Based on the previous estimation results, the interaction variables use *log(RESIDP)* instead of *RESIDP*. Table 2.3 reports the estimation outcomes of models using interaction variables, based on the model in column #6 of Table 2.2. Though the household income and *log(RESIDP)* turn out to be insignificant, their interaction variables with *log(RESIDP)* show positive impacts at the 5% significance level. This means that higher income households are likely to increase their energy use as their tenure in their homes increases. However, the interaction variable between electricity price and residence period has no significance in column #2 of Table 2.3, while the coefficients for price elasticity remain negative.

By contrast, the interaction variables using *HDD* and *CDD*, which are shown in columns #3 and #4, respectively, of Table 2.3, are found to have negative coefficients, while the effects of *log(RESIDP)*, *HDD*, and *CDD* remain positive. Column #5, which includes both *HDD* and *CDD*, repeats the results. This indicates that climate conditions have some effects on the differences in dynamics of energy consumption between new movers and stayers. Specifically, the greater the gap between *HDD* and *CDD*, the larger the gap is between movers and stayers. For instance, comparing new movers and 20-year stayers, electricity consumption shows an approximately 6.3% difference in the Houston SMSA, where the average *HDD* is 1,930 and the average *CDD* is 2,918, but this gap widens to 24.5% in the San Francisco-Oakland SMSA, where the average *HDD* is 2,389 and the average *CDD* is 953. This is probably because the severe climate in the Houston SMSA forces residents to use a certain amount of electricity (especially for cooling), and hence, there is less flexibility to change their energy patterns over time.

Table 2.4 presents results that add interaction variables using household and housing characteristics. Ownership, single-family housing, and unit size interaction variables are found not to have a significant interaction effect with *log(RESIDP)* statistically. The interaction variable using the number of household members has a positive coefficient, indicating that larger households tend to increase their energy consumption faster, as they stay in their homes longer than do smaller households. Although the single-family housing unit variable and the owner variable are not significant, their combined effect (i.e., single-family owner-occupied housing unit) can have a unique effect. Therefore, the last column adds the interaction variables between

Table 2.3 Interaction Effects between Residence Periods and Economic/Climate Variables

	(1)	(2)	(3)	(4)	(5)
log(RESIDP)	-0.032	-0.009	0.058 ***	0.052 ***	0.151 ***
log(RESIDP)×log(HHINC)	0.006 **				
log(RESIDP)×log(PRICE)		0.019			
log(RESIDP)×HDD			-0.004 **		-0.016 ***
log(RESIDP)×CDD				-0.009 **	-0.034 ***
log(HHINC)	-0.011	0.005	0.005	0.005	0.005
log(PRICE)	-0.449 ***	-0.495 ***	-0.443 ***	-0.453 ***	-0.439 ***
HDD	0.059 ***	0.061 ***	0.074 ***	0.058 ***	0.104 ***
CDD	0.075 ***	0.077 ***	0.076 ***	0.099 ***	0.161 ***
log(PER)	0.206 ***	0.207 ***	0.207 ***	0.206 ***	0.206 ***
OWNER	-0.046 ***	-0.047 ***	-0.048 ***	-0.046 ***	-0.046 ***
YOUNG	-0.051 ***	-0.052 ***	-0.052 ***	-0.051 ***	-0.052 ***
ELDER	-0.016 *	-0.016 *	-0.015	-0.017 *	-0.015
HIGHEDU	-0.006	-0.007	-0.007	-0.007	-0.007
log(UNITSF)	0.065 ***	0.065 ***	0.064 ***	0.066 ***	0.065 ***
ROOMS	0.020 ***	0.020 ***	0.020 ***	0.020 ***	0.019 ***
HELEC	0.119 ***	0.119 ***	0.118 ***	0.119 ***	0.117 ***
COOK	0.057	0.058	0.058	0.056	0.058
REFR	-0.046	-0.044	-0.045	-0.045	-0.045
DISH	0.056 ***	0.056 ***	0.056 ***	0.056 ***	0.056 ***
WASH	0.088 ***	0.087 ***	0.086 ***	0.088 ***	0.089 ***
AIR	0.029 ***	0.029 ***	0.029 ***	0.029 ***	0.029 ***
AIRSYS	0.056 ***	0.056 ***	0.056 ***	0.056 ***	0.056 ***
Obs.	32,382	32,382	32,382	32,382	32,382
Adj. R^2	0.671	0.671	0.671	0.671	0.671

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Table 2.4 Interaction Effects of Residence Periods and Housing/Household Variables

	(1)	(2)	(3)	(4)	(5)
log(RESIDP)	0.014 *	0.029 ***	0.035 ***	0.018	0.020 *
log(RESIDP)×log(PER)	0.031 ***				
log(RESIDP)×OWNER		0.014			0.046 **
log(RESIDP)×SINGLE			0.006		0.021
log(RESIDP)×log(UNITSF)				0.003	
OWNER×SINGLE					0.035
log(RESIDP)×OWNER×SINGLE					-0.045 *
log(HHINC)	0.004	0.005	0.005	0.005	0.005
log(PRICE)	-0.448 ***	-0.450 ***	-0.450 ***	-0.450 ***	-0.450 ***
HDD	0.060 ***	0.059 ***	0.059 ***	0.059 ***	0.060 ***
CDD	0.077 ***	0.076 ***	0.075 ***	0.075 ***	0.076 ***
log(PER)	0.139 ***	0.206 ***	0.207 ***	0.207 ***	0.206 ***
OWNER	-0.051 ***	-0.071 ***	-0.047 ***	-0.047 ***	-0.093 *
YOUNG	-0.041 ***	-0.052 ***	-0.052 ***	-0.052 ***	-0.052 ***
ELDER	-0.014	-0.017 *	-0.016 *	-0.016 *	-0.017 *
HIGHEDU	-0.012	-0.007	-0.007	-0.007	-0.007
log(UNITSF)	0.064 ***	0.065 ***	0.065 ***	0.058 *	0.065 ***
ROOMS	0.019 ***	0.020 ***	0.020 ***	0.020 ***	0.020 ***
HELEC	0.120 ***	0.119 ***	0.119 ***	0.119 ***	0.119 ***
COOK	0.056	0.056	0.057	0.057	0.057
REFR	-0.044	-0.046	-0.045	-0.045	-0.045
DISH	0.056 ***	0.056 ***	0.056 ***	0.056 ***	0.056 ***
WASH	0.089 ***	0.087 ***	0.087 ***	0.087 ***	0.088 ***
AIR	0.028 ***	0.029 ***	0.029 ***	0.029 ***	0.029 ***
AIRSYS	0.055 ***	0.056 ***	0.056 ***	0.056 ***	0.056 ***
Obs.	32,382	32,382	32,382	32,382	32,382
Adj. R^2	0.671	0.671	0.671	0.671	0.671

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

OWNER, *SINGLE*, and *log(RESIDP)*. The result indicates that new movers who own their homes use less energy (*OWNER* = -0.093), but the gap decreases as they live in those homes longer (*log(RESIDP)*×*OWNER* = 0.046). However, in a single-family housing unit, this impact from homeownership is almost offset (*log(RESIDP)* × *OWNER* × *SINGLE* = -0.045). These dynamic relationships with *log(ELEC)* are compared in Figure 2.3. It is notable that after a seven-year stay, the increase in energy consumption of an owner-occupied multifamily housing unit surpasses that of a renter-occupied housing unit. There are several possible explanations, but this study suggests that the phenomenon is due to split incentives, which are deeply explored in the next chapter of this dissertation.

Comparison between movers and stayers. Similar to Sonderegger (1978), this study additionally conducts a straightforward comparison of movers and stayers in terms of their residential energy consumption. More specifically, it compares the effects of residence change by focusing on movers, defined as individuals who moved in 2006-2007, which divides the study period in half (2001-2005 and 2008-2013). Thus, this study obtains a mover group, with 120 housing units (840 observations in total), and a stayer group, with 2,149 housing units (15,043 observations in total).

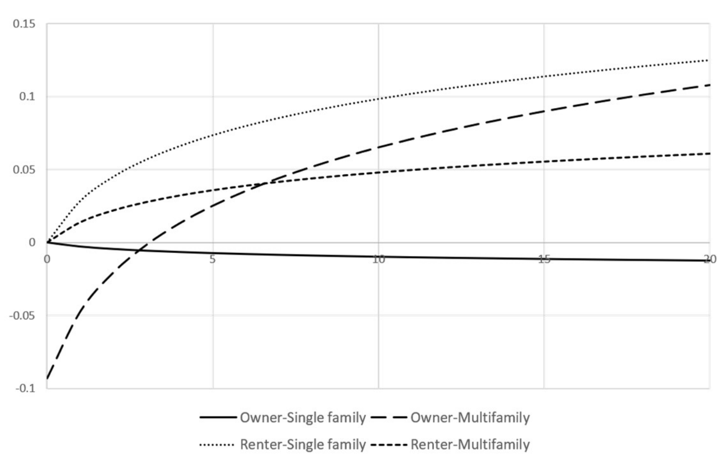


Figure 2.3 Effects of Residence Period on Electricity Consumption by Housing Type and Ownership Structure

Table 2.5 Comparison Between Movers and Stayers

	Entire Period (Pooled)		Entire Period (Fixed-effect)		Pre-2006 (Pooled)		Post-2007 (Pooled)	
	Mover	Stayer	Mover	Stayer	Mover	Stayer	Mover	Stayer
Intercept	1.494 **	0.871 ***			1.546 **	0.868	1.953 ***	1.038 ***
log(HHINC)	0.021	0.031 ***	-0.008	0.003	0.060 **	0.037 ***	0.013	0.033 ***
log(PRICE)	-0.930 ***	-0.527 ***	-0.589 **	-0.421 ***	-1.106 ***	-0.735 ***	-0.924 ***	-0.574 ***
HDD	0.047 ***	0.029 ***	0.099	0.018	0.013	0.015 ***	0.065 ***	0.028 ***
CDD	0.200 ***	0.151 ***	-0.083	0.014	0.118 **	0.124 ***	0.221 ***	0.150 ***
log(PER)	0.210 ***	0.238 ***	0.192 ***	0.195 ***	0.177 ***	0.205 ***	0.214 ***	0.282 ***
OWNER	0.103	0.045 *	0.238 ***	0.078 **	0.147 *	0.094 ***	0.093	0.0003
YOUNG	-0.082	-0.096 ***	-0.070	-0.070 ***	0.025	-0.049 **	-0.240 ***	-0.044
ELDER	-0.013	0.003	0.008	-0.015	0.068	-0.017	-0.007	-0.016
HIGHEDU	0.009	-0.036 ***	0.002	-0.019	0.052	-0.039 **	-0.079	-0.041 **
log(UNITSF)	0.163 ***	0.116 ***	-0.038	0.076 **	0.201 ***	0.110 ***	0.104 *	0.109 ***
ROOMS	0.031 **	0.054 ***	0.022	0.019 ***	0.016	0.051 ***	0.055 **	0.064 ***
HELEC	0.280 ***	0.333 ***	0.078	0.107 ***	0.369 ***	0.307 ***	0.161 *	0.321 ***
DUPLEX	0.316 ***	-0.014			0.285 **	-0.036	0.291 ***	0.042
APARTMENT	-0.086	-0.203 ***			0.019	-0.182 ***	-0.153	-0.187 ***
BLDAGE	0.0025 **	0.0009 ***			0.0009	-0.0001	0.0020	-0.0002
COOK	-0.012	0.002	0.00 9	0.124	-0.138	-0.137		0.062
REFR		-0.010		0.147		0.713		0.029
DISH	0.044	0.143 ***	-0.086	0.088 ***	0.068	0.140 ***	0.063	0.119 ***
WASH	0.088	0.062 **	0.102	0.093 **	0.087	0.042	0.098	0.086 **
AIR	0.162 ***	0.133 ***	0.075	0.001	0.267 ***	0.144 ***	0.179 **	0.165 ***
AIRSYS	0.275 ***	0.214 ***	0.043	0.045 **	0.242 ***	0.192 ***	0.252 ***	0.192 ***
Obs.	840	15,043	840	15,043	360	6,447	360	6,447
Adj. R^2	0.436	0.377	0.670	0.678	0.442	0.401	0.454	0.406

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

According to the results, which are based on all years from each sample group shown in the first and second columns of Table 2.5, the price elasticity of the movers is higher than that of the stayers. In the pooled model, movers have a greater magnitude of price elasticity (-0.930, significant at 1% level) than do stayers (-0.527, significant at 1% level), as in the fixed effect model (-0.589 vs. -0.421). In addition, *log(PER)* also exhibit higher coefficients in the stayer group.

Moreover, this study conducts a pooled panel analysis on observations pre-2006 and post-2007, as shown in columns #4 and #5 of Table 2.5. Both movers and stayers are found to have smaller price elasticities in the "post" period, but the change is greater in the stayer group (-21.9%) than it is in the mover group (-16.5%). This means that stayers are more reluctant to modify their energy use patterns in response to price changes, implying that some inertia may exist among stayers that discourages a substantial shift in their lifestyle. Additionally, while coefficients for *HDD* and *CDD* present similar values in both groups in the pre-2006 period, the mover group has significantly greater coefficients in the post-2007 period, suggesting that movers are more likely to be influenced by climate conditions. It is also notable that the coefficient for the income variable is significant in both groups pre-2006, but it becomes significant only in the stayer group post-2007, suggesting that household income may come into play when households do not choose relocation as a response to income changes.

Quasi-experimental analysis. While the analysis above compares movers and stayers directly and offers some interesting findings, it may have potential selection biases. To avoid this potential problem, a pair matching technique is employed using the Mahalanobis distance to determine the differences between movers and stayers based on the paired observations. This measure presumes that variables used for calculating distances and similarity can be correlated, while Euclidian distance assumes they are uncorrelated, and accounts for covariance between variables and differences in variance in each direction. This notion can be compared to an ellipse, while Euclidian distance can be compared to a circle that has identical variances in all directions, as shown in Figure 2.4 (De Maesschalck et. al., 2000). The mathematical definition of the Mahalanobis distance between two observations is as below:

$$D_M = \sqrt{(x-y)C^{-1}(x-y)^T}$$

where *x* and *y* are vectors of each observation, C^{-1} is covariance matrix of variables, and *T* denotes the transpose matrix. If C^{-1} is an identity matrix, this equation is reduced to a Euclidian distance calculation.

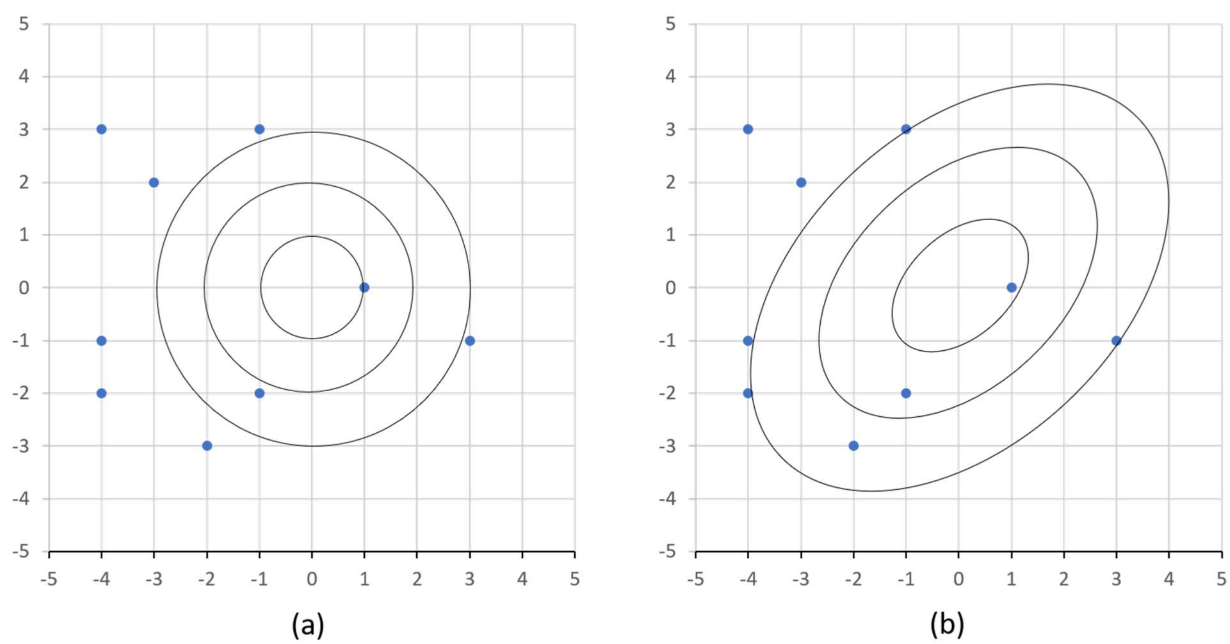


Figure 2.4 Visual Comparison between (a) Euclidian Distance and (b) Mahalanobis Distance

Specifically, this study uses a matching process that first restricts several conditions that are identical, such as SMSA code, housing unit type, main heating fuel, and homeownership. Then, Mahalanobis distances between observations in treatment group and observations in control group are calculated using variables including *HHINC*, *PER*, *YOUNG*, *ELDER*, *DISH*, and *WASH*. In other words, any pairs generated by this matching process are located in the same SMSA area and have identical conditions of housing unit type, heating fuel, and homeownership, and they have similarities in income, household size, presence of a young child or elderly person, and ownership of a dishwasher and washing machine. As a result, 98 pairs of unique housing units are generated, and the descriptive statistics are presented in Table 2.6.

Given the significant decrease in sample size, from 4,626 unique housing units to 196 unique housing unit observations, a potential issue is the small sample size. To address this problem, this study focuses on the results from the pooled model (OLS), which can increase the degrees of freedom. Specifically, 686 observations per group were used for the whole study period, and 294 observations per group were used in the pre- and post- 2006/2007 models. Additionally, ample attention is paid to comparisons between models, such as a comparison with the previous mover vs. stayer model without a matching method or a comparison between pre- and post- models.

The results in Table 2.7 echo the differences – shown in the previous findings in Table 2.5 – between movers and stayers regarding price elasticity. However, when the pair-matching technique is applied, the difference becomes smaller than that from the estimation results. Still, the fixed effect model yields statistical significance for price elasticity in the mover group only. The effects of the number of household members and the use of electricity as a main heating fuel

Table 2.6 Comparative Descriptive Statistics Between Mover-Stayer Pairs

	Mover (n = 686 [a])				Stayer (n = 686)			
	Mean	St. Dev.	Minimum	Maximum	Mean	St. Dev.	Minimum	Maximum
ELEC	8.74	6.02	0.58	41.76	9.83	7.12	0.52	61.59
HHINC	95052	92916	3	972106	98262	91489	100	941746
PRICE	13.18	3.44	7.52	36.98	13.18	3.44	7.52	36.98
HDD	4674	1989	0	9162	4674	1989	0	9162
CDD	1196	895	223	4754	1196	895	223	4754
PER	2.64	1.35	1	9	2.50	1.24	1	7
OWNER	0.88	0.33	0	1	0.90	0.30	0	1
YOUNG	0.19	0.40	0	1	0.11	0.31	0	1
ELDER	0.27	0.44	0	1	0.37	0.48	0	1
HIGHEDU	0.80	0.40	0	1	0.74	0.44	0	1
UNITSF	1707	740	140	10099	1796	808	200	4000
ROOMS	6.28	1.63	1	14	6.25	1.71	3	15
HELEC	0.12	0.32	0	1	0.11	0.31	0	1
SINGLE	0.88	0.33	0	1	0.88	0.33	0	1
DUPLEX	0.05	0.22	0	1	0.05	0.22	0	1
APARTMENT	0.07	0.26	0	1	0.07	0.26	0	1
COOK	1.00	0.00	1	1	1.00	0.04	0	1
REFR	1.00	0.00	1	1	1.00	0.04	0	1
DISH	0.71	0.46	0	1	0.68	0.47	0	1
DRY	0.90	0.30	0	1	0.90	0.30	0	1
WASH	0.92	0.27	0	1	0.93	0.26	0	1
AIR	0.27	0.45	0	1	0.28	0.45	0	1
AIRSYS	0.64	0.48	0	1	0.69	0.46	0	1
BLDAGE	51.97	21.95	1	94	52.96	20.84	6	94

[a] 98 housing units × 7 years

Table 2.7 Estimation Results Between Mover-Stayer Pairs

	Entire Period (Pooled)		Entire Period (Fixed-effect)		Pre-2006 (Pooled)		Post-2007 (Pooled)	
	Mover	Stayer	Mover	Stayer	Mover	Stayer	Mover	Stayer
Intercept	1.703 ***	0.318			1.643 **	3.476 ***	2.419 ***	-0.420
log(HHINC)	0.022	0.055 **	-0.006	0.007	0.054 *	0.048	0.017	0.087 **
log(PRICE)	-0.874 ***	-0.767 ***	-0.634 **	-0.309	-1.181 ***	-1.054 ***	-0.839 ***	-0.710 ***
HDD	0.036 **	-0.016	0.092	-0.112	0.024	-0.026	0.041 *	-0.022
CDD	0.177 ***	0.062	-0.092	0.005	0.140 **	0.037	0.189 ***	0.081
log(PER)	0.189 ***	0.203 ***	0.177 ***	0.251 ***	0.152 **	0.139 *	0.126 **	0.235 ***
OWNER	0.167 **	0.024	0.231 **	0.026	0.109	0.045	0.125	0.099
YOUNG	-0.104 *	-0.070	-0.093	-0.117	0.032	-0.053	-0.179 **	-0.033
ELDER	-0.052	0.156 ***	-0.007	0.051	0.059	0.180 **	-0.086	0.073
HIGHEDU	-0.008	0.143 **	-0.064	-0.038	0.040	0.123	-0.081	0.103
log(UNITSF)	0.146 ***	0.036	-0.060	0.017	0.196 ***	-0.055	0.075	0.082
ROOMS	0.044 ***	0.082 ***	0.022	0.057 ***	0.027	0.075 ***	0.094 ***	0.100 ***
HELEC	0.273 ***	0.375 ***	0.062	-0.151	0.339 ***	0.196 *	0.206 **	0.421 ***
DUPLEX	0.199 **	-0.144			0.138	-0.108	0.175	-0.139
APARTMENT	-0.179	-0.137			0.160	-0.137	-0.480 **	-0.416
BLDAGE	0.0023 *	0.0008			0.0005	-0.0033 *	0.0023	0.0024
COOK		1.015 *		1.197 **				1.053 *
REFR		0.492		0.219				0.707
DISH	0.050	-0.094	-0.117	-0.051	0.074	-0.079	0.013	-0.111
WASH	-0.088	0.288 *	0.036	0.545 **	0.136	0.358 *	-0.258	-0.097
AIR	0.071	0.169 **	0.047	0.070	0.195 **	0.207 **	-0.026	0.115
AIRSYS	0.187 ***	0.214 ***	0.027	0.159	0.180 *	0.226 **	0.098	0.075
Obs.	686	686	686	686	686	686	686	686
Adj. R^2	0.379	0.361	0.646	0.651	0.399	0.429	0.396	0.340

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

are also found to be greater in the stayer group, which is consistent with the results in the previous comparison model without a matching method.

In regard to the comparison of the pre-2006 and post-2007 subsamples, shown in columns #3 and #4, the changes in the effects of price elasticity and the number of household members also continue to show a similar pattern. More specifically, regarding the price elasticity, the mover group has decreased by a factor of 29% in magnitude (from -1.181 to -0.839), while the stayer group has decreased by a factor of 33% (from -1.054 to -0.710). This indicates that the movers who relocated during 2006-2007 exhibit greater price elasticity in the post-2007 period. Further, it should be highlighted that while the coefficient for *log(PER)* shows a slight difference between the two groups in the pre-2006 period (0.152 vs. 0.139), but post-2007, the stayer group has a considerably higher coefficient than the mover group (0.126 vs. 0.235). This result supports the finding of the previous analysis that stayers with a larger household size increase their energy consumption faster as they stay longer in the same dwelling unit.

Conclusion

This study investigates the dynamics of residential energy use that are linked to households' relocation and their period of residence. The findings from the empirical analysis using the AHS from 2001 to 2013 reveal that residential energy consumption is associated with the length of residence in a dwelling unit. Specifically, residents who have recently moved tend to use less electricity than households who have lived in the same dwelling unit for a longer period of time. In addition, as their period of residence increases, they are likely to consume more energy; in particular, consumption increases faster in the early period and becomes slower as time elapses (i.e., linear-log graph).

One possible explanation is that residents tend to accumulate appliances the longer they live in one place, until they reach a certain level at which they are satisfied. This adjustment towards greater satisfaction requires some trial-and-error and a learning period to understand the characteristics of the surrounding environment and the available options that best serve a resident's quality of life. Once households settle into their lifestyles with certain patterns of energy use, they tend to maintain their energy consumption patterns and be less responsive to changes in external conditions. This is relevant to the theory of behavioral economics discussed in Chapter 1, particularly the "anchoring" or default effect, which reduces cognitive burdens during decision-making (Tversky and Kahneman, 1974; Samuelson and Zeckhauser, 1988).

Additionally, this energy consumption pattern can be explained by the notion of triggering, as argued by Fogg (2009). When residents move to new homes, they are more likely to be exposed to information about energy efficiency, as they may need to purchase new appliances. This exposure can function as a trigger that brings residents' attention to pro-environmental norms and leads them to behave in more environmentally friendly ways, such as by purchasing appliances with better efficiency despite higher prices, and consequently energy consumption in homes decreases. As the residents live longer in the housing unit, however, the triggered norms gradually use their influence, and energy consumption increases.

This study also finds that the period of residence influences how various socio-economic factors and external conditions are associated with energy consumption. A higher household income accelerates the increase in energy consumption during the period of residence, suggesting that greater disposable income provides households with more leeway to change their energy use patterns, especially by increasing their energy use. However, a severe climate tends to reduce the increase (or adjustment) speed, perhaps because extreme weather establishes higher baselines of residential energy consumption, and hence, people have less freedom to increase their energy use over time. Furthermore, along with the period of residence, various combinations of tenure and housing unit types are found to have different energy consumption change patterns. To some extent, this finding could be attributed to the problem of split incentives, which is investigated in the next chapter.

The results using the quasi-experimental setting also examine the different energy use patterns of residents who move to new homes compared to residents who do not move to new homes. It is found that the former group (movers) is more responsive to electricity price changes compared to the latter (stayers), while the energy consumption of stayers is more influenced by the number of household members when other confounding factors are controlled, implying that the characteristics of these dynamics can change over the course of the residence period.

Overall, the results imply that residential energy consumption is a truly dynamic process even at a micro (household) level, and this dynamic process is shaped not only by a wide range of determinants of energy consumption ranging from human factors (e.g., income, age, and homeownership) to external conditions (e.g., weather, energy price, and housing unit size) but also by the dynamic interactions between residents and their surroundings. More specifically, residents who are more familiar with their surrounding physical conditions are less reactive to external factors, such as energy price and climate, but they are more likely to change their energy consumption due to internal factors, such as the number of household members.

From the perspective of policy-makers, this complicated nexus of energy consumption, housing, and residents' behaviors is difficult to address. However, it is worth focusing on this complexity because it is useful in developing more effective residential energy policies, specifically in areas with high household mobility and those with lower mobility (see, e.g., Dieleman et al., 2000; Kim 2014). For instance, policy-makers may focus on more aggressive energy price policies in highly mobile residential areas while concentrating their efforts on behavioral approaches, such as energy conservation campaigns, in areas where residents are less likely to migrate.

Admittedly, this study is not without limitations. First, one could question the validity of the measurements used in this study. Because the energy consumption data of the AHS are based on a household's subjective calculations (i.e., "What is the average monthly cost for electricity?"), measurement errors may exist. Furthermore, detailed multipart tariff schedules, which complicate the effect of electricity price on actual energy consumption, were not thoroughly considered due to data limitations. In some states, including California, the price of electricity is not linearly associated with the amount of electricity used. Instead, if residents use more than a certain amount of energy, they must pay a higher rate. In this case, consumers' utility-maximization behavior depends not only on the average electricity price but also on the entire price schedule (Reiss and White, 2005). Therefore, in this case, using the average electricity price would not be a perfect way to investigate (or control for) pricing effects.

Despite these limitations, this study attempts to expand our knowledge base regarding the nature of residential energy consumption, with a focus on dynamic interactions between households and their dwelling units. It provides useful insights into the micro-level dynamics of residential energy consumption by investigating how energy consumption is associated with the period of residence. However, this study is limited in that it observes housing units, and due to considerable challenges in data collection, it cannot reflect the multiple relocation events that many households experience in the real world. If they can overcome the limitations of data collection, future studies may investigate how households modify their energy consumption patterns differently in response to experiencing multiple relocations over the course of their life cycle. Additionally, employing a more refined sample selection could advance this study: for instance, relocated households could be categorized by origin and destination climate (e.g., from a cold region to a hot region) or by the main reason for moving (e.g., for a bigger home or foreclosure).

CHAPTER 3

Barriers to Adoption of Solar Energy Systems:

Split Incentives and Split Decision-Making

Introduction

In recent years, there has been growing concern about the economic and environmental threats associated with heavy dependence on fossil fuels. Alternatives to fossil fuels include various sources of so-called renewable energy, such as sunlight, wind, tides, and geothermal heat. Among these, solar energy is one of the most plentiful and popularized, and there have been numerous attempts to promote the adoption of solar energy systems. These attempts have included incentive programs (e.g., the Federal Energy Management Program) and collaborations between public and private sectors (e.g., the Open PV Project). However, despite these efforts, adoption of solar energy systems has remained low, even in areas where large incentives and subsidies have been provided to promote the wide dissemination of such systems (see, e.g., Bauner and Crago, 2015). Specifically, while the U.S. has experienced rapid growth in solar energy production since 2013, with an average annual increase of 34%, solar energy only accounted for 0.5% of total energy production in 2016, and the percentage in the residential sector was much smaller (0.1%).

This slow adoption of solar energy systems despite abundant incentives can be attributed to various obstacles, such as lack of information, regulatory barriers, negative perceptions, and market failures (Jaffe and Stavins, 1994; Reddy and Painuly, 2004; Owen, 2006). For instance, both lack of information about new technologies/incentives and personal/institutional inertia increase perceived costs and discourage the adoption of alternative energy systems. When the market prices of "dirty" energy do not reflect the associated negative environmental externalities, the comparative advantages of clean solar energy can hardly increase. Additionally, due to the difficulty of forecasting future scenarios, such as future economic conditions and energy prices, the risks that consumers perceive can differ from actual risks, especially when an investment has long-term returns.

Among these barriers, the problem of split incentives has been attracting increasing attention not only because it has significant and detrimental effects on investments in energy efficiency but also because it presents a unique difficulty that technological approaches cannot solve (Murtishaw and Sathaye, 2006; Gillingham et al., 2012). Specifically, it is argued that tenants who do not directly pay utility fees tend to be neglectful of energy-efficient appliances, while landlords who charge their tenants utility fees are less interested in investing in energy-efficient appliances than are landlords who pay those fees themselves. In the case of solar energy systems, which are generally installed on buildings – unlike appliances, which are generally installed inside individual housing units – complication in decision-making among multiple agents sometimes comes into play with adoption, especially in contexts of shared property, such as multifamily buildings (Altmann, 2014; Puustinen et al., 2015). In this case, hereafter referred to as split decision-making, the decision-making process is divided in accordance with the various interests and preferences of different owners, and the costs of collective decision-making rise significantly.

While there are studies of each of these individual problem cases, little is known about how these inter-agent dynamics – in combination with each other – influence solar energy system adoption in residential buildings. To fill this gap, this study investigates the effects of these complicated situations by focusing specifically on split incentives and split decision-making as they relate to choices of solar energy systems in residential buildings.

Literature Review on Split Incentives and Split Decision-making

Economists have long been interested in split incentives, or the principal-agent problem (see, e.g., Grossman and Hart, 1983). Recently, given the increased importance of energy conservation, more attention is being paid to the role of split incentives in energy efficiency and the degree to which the problem is related to inefficient energy consumption patterns. In one notable study, Murtishaw and Sathaye (2006) classified households into four distinct categories based upon a two-by-two matrix (direct vs. indirect energy payments and choice vs. no choice of appliances) and investigated the effects of split incentives on final and primary energy consumption. More specifically, they hypothesized that households who pay energy costs directly but are not able to choose their devices have an efficiency problem, as they can be forced to use less energy-efficient appliances. Households who do not pay their energy bills directly but are able to choose their own devices may have a usage problem because having zero marginal energy costs influences them to use energy excessively. If households can choose their devices but do not pay energy costs, they have both problems: that is, they may tend to choose inefficient appliances and excessively consume energy. Households who pay utility fees directly and are able to choose appliances are the only category without any split incentive issues. Using this framework and data from the AHS, Murtishaw and Sathaye analyze the impacts of split incentives on four major end-use residential energy consumption sectors: refrigeration, water heating, space heating, and lighting. The results show that a considerable proportion of residential energy is affected by the problem of split incentives. Indeed, approximately 35% of their sample, or 48% of total energy use, was subject to the problem.

This finding has been supported by several empirical studies that use similar frameworks. For instance, using data from the RECS in the U.S., Gillingham et al. (2012) have found that tenants who pay their own heating energy bills are more likely to turn down the heat at night by a factor of 13%, and their heating temperature settings are lower than those of households who do not pay heating bills. In addition, owner-occupied dwelling units in which residents pay for space heating and cooling (which are regarded as having no split incentive issues in Murtishaw and Sathaye's classification) are 20% more efficient in their ceiling insulation and are 13% better insulated in their exterior walls. Similarly, De T'Serclaes (2007) identifies the split incentive problem for space heating in houses with different tenure statuses by analyzing residential energy data from the Netherlands. According to the results, which cover a period between 1993 and 2002, gaps in exterior (roof, wall, and floor) insulation between owner-occupied and renter-occupied houses range from 18% to 30%, and approximately 40% of the energy used for space heating in the residential sector is consumed in a situation that is subject to the split incentive problem.

Other studies have focused on specific dimensions of the split incentive issue, such as owner vs. renter or utility-paying vs. non-paying. For instance, Levinson and Niemann (2004) compare two tenant groups, categorized by utility payment status in rental housing units, with the focus on heating energy consumption. While renters with direct utility payments have no split incentive problem, tenants who do not pay utility fees directly have less incentive to conserve energy, and consequently landlords are likely to increase rental rates to offset the higher energy consumption resulting from tenants' use behaviors. Although utility-included housing can make tenants or landlords, or both, worse off than if they had used individual metering units, this seemingly no-win situation can be explained from both landlords' and tenants' perspectives. According to the authors, including utility fees in tenants' rent can reduce costs for metering and lead to economies of scale on the landlord's side. At the same time, risk-averse tenants are more likely to choose utility-included units to avoid fluctuating monthly utility costs. The results report that utility costs in utility-included rental housing are greater than utility costs in utility-metered rental housing, but the gap is not substantial.

In addition, using multi-family housing unit data from Canada, Maruejols and Young (2011) examine differences in temperature settings between the two distinct utility payment statuses, and they find evidence of split incentives to be a cause of inefficient energy consumption patterns in multifamily housing units. Specifically, compared to residents who pay utility costs directly and are thus unaffected by split incentives, residents who do not pay heating energy costs tend to set their thermostats at higher temperatures. Additionally, residents subject to split incentives are less likely to turn down their heat when no one is present in the house or when the cold is less severe.

Focusing on ownership structures, Davis (2011) investigates the differences between owners and renters in their adoption rates of energy-efficient appliances. He discovers that renters tend to have significantly less-energy-efficient refrigerators (6.7 to 8.2%), dishwashers (9.7 to 15.7%), air conditioners (3.2%), and laundry machines (3.0 to 6.7%) when household income and other household characteristics are controlled. This inefficiency occurs because landlords tend to provide cheap and inefficient appliances in homes where their tenants pay the utility bills. One could argue that landlords should provide more energy-efficient appliances and charge higher rents to compensate the investment, but this is unlikely to happen due to difficulties in convincing tenants that potential energy savings can offset rent increases. According to the author, it is also difficult for tenants to evaluate cost savings from energy-efficient appliances because they may not have enough experience with or information about the benefits of energy-efficient appliances.

Similarly, using OECD survey data (EPIC: Environmental Policy and Individual Behavior Change) from eleven countries, Krishnamurthy and Kristrom (2015) examine the effects of split incentives between owners and renters on the adoption of various energy-efficient technologies in residential sectors. The technologies they survey include energy-efficient appliances, energy-efficient bulbs, ground source heat pumps, thermal insulation, heat thermostats, wind turbines, energy-efficient windows, and solar panels. The authors discover a substantial variation in adoption rates across these energy-efficient technologies. For instance, owners are more likely than renters to install energy-efficient bulbs by a factor of 50%, whereas heat thermostat adoption shows a smaller gap (1%). Despite these variations, the results suggest that split incentives generally hinder the adoption of various energy-efficient technologies in residential sectors.

In addition to split incentives by tenure and utility payment status, there is another dimension that affects the adoption of solar energy systems. Solar energy systems are similar to energy-efficient appliances in that they require meaningful initial investments and subsequently provide long-term returns in the form of reduced energy costs. However, a critical difference is that solar panels are attached to the housing units semi-permanently, and thus decision-making on the installation is subject to the consideration of the expected duration of residence and the resident's long-term financial situation. This may drastically increase the cost of the decision-making process, especially when multiple agents (homeowners) with heterogeneous preferences are involved and collective decision-making is required to reach an agreement among a number of property owners.

As Altmann (2014) notes, when agents are involved in a split decision-making situation, “one of the owners needs to take on the leadership role, and have the skills [to] effectively negotiate an outcome” (p. 447). This requirement, in turn, significantly increases the complexity and the transaction costs. Even if there is an active governance system such as a resident committee, low participation of residents can undermine trust and decision-making capacity, and short-term owners sometimes decline to invest in energy-efficient systems that have long-term benefits. In addition, despite the availability of sufficient federal government grants promoting the profitability of solar energy systems, some homeowners are not eligible for standard government rebates because the shared property is owned by separate legal entities.

A similar argument is advanced by Puustinen and Viitanen (2015) with respect to infill development near multi-owner residential buildings. Their case study identifies three major challenges: legal issues, difficulties in collective action management, and a lack of qualified professionals. The authors note that a high voting threshold can lead to a “hold-out” situation and consequently dampen collective decision-making. Additionally, different interests among owners complicate the situation. For instance, occupier-owners who intend to continue to live in the homes seek long-term capital gains and property improvements, and consequently they are more open to investment in solar energy systems. However, investor-owners, who purchase dwelling units merely for profit, are reluctant to spend on improvements unless they guarantee short-term investment gains. Furthermore, the ability to resolve legal constraints and access to professional knowledge are essential elements when trying to reach an agreement. These findings are consistent with Altmann's argument with regard to demonstrating the difficulties of decision-making in collectively owned dwelling units.

In summary, the literature identifies two major problems that discourage the adoption of solar energy systems. The first is the problem of split incentives, which occurs when residents who determine energy consumption do not pay their own energy costs or when landlords who do not pay energy costs determine the energy-efficiency of residential buildings. Additionally, the problem of split decision-making among owners can discourage energy-efficient behaviors, especially when such behaviors are related to shared properties and significant collaborative efforts are required to make an agreement. To the best of my knowledge, although some studies have noted the effects of each problem, no attention has been paid to how these two issues, in combination, influence the adoption rates of solar energy systems. To fill this gap, this study identifies various situations relevant to solar energy system choices, with a focus on housing type, ownership structure, and utility payment arrangement, and it empirically analyzes how these inter-agent dynamics (i.e., split incentives and split decision-making) influence the adoption of solar energy systems.

Analytic Framework, Model, Variables, and Data

Analytic framework and model. To empirically investigate how complications in the two focus factors (i.e., split incentives and split decision-making) affect the adoption of solar energy systems, this study employs a logistic regression model. This model has the dependent variable in a binary form; in particular, a positive response to using solar energy is encoded as 1 and otherwise as 0. The model below briefly describes the logistic regression model of this study:

$$logit(p) = \ln\left(\frac{p}{1-p}\right) = \beta_1 \cdot X_i + \sum \beta_n \cdot Z_{n,i} + \varepsilon_i$$

where p is the probability of adopting a solar energy system, $\left(\frac{p}{1-p}\right)$ is the odds ratio, X_i is a set of key explanatory variables, i.e., tenure status, housing unit type, and utility payment status, and $Z_{n,i}$ represents a set of control variables that may have significant influences on the rate of solar energy system adoption, as described above. β_1 and β_{n} are sets of coefficients for key variables and control variables, respectively, and ε_i is the error term.

For the empirical analysis, it is first hypothesized that split incentives between tenants and landlords take place based on ownership structure and utility payment status. If a dwelling unit is owner-occupied and the residents pay utility costs, no issues from the split incentives are found. However, if a dwelling unit is occupied by a renter who pays utility bills, inefficiency due to split incentives may exist because landlords are reluctant to invest in energy-efficient systems, even though tenants suffer from higher energy costs due to less efficient energy systems. In regard to owner-occupied housing units where residents do not pay utility bills, there are fewer incentives for homeowners to install solar energy systems that can save energy costs in the long run. Lastly, there are split incentives caused by both a lack of incentives and the inability to choose energy systems in renter-occupied housing units where utility bills are not charged to the tenants.

Another factor considered in this study is split decision-making, which arises when a household does not have full control over its residential building. In such cases, installation of solar energy systems can therefore potentially cause conflicts among the multiple owners who share the property and have various interests. More specifically, as noted in the literature, apartment buildings with multiple owners, representing the so-called "split decision-making" scenario, require an agreement among the majority of residents to install solar panels on the building's roof. In contrast, owners of single-family housing units need not go through this process. Therefore, it is hypothesized that owner-occupied and single-family homes are more likely to have solar energy systems.

Given these two discrete classifications, the purpose of this study is to take them into account together and investigate how each combination of split incentives and split decision-making influences solar energy adoption. Figure 3.1 and Table 3.1 briefly present eight categories of the combinations formed by three key variables: tenure, utility payment structure, and housing unit type.[7]

Among the eight categories, only one is not affected by split incentives and split decision-making issues. In housing units categorized as OPS (owner-occupied, paying for utilities, and single-family), serving as the baseline of the empirical analysis, the residents have both the incentives and the ability to install solar panels. In other words, having a solar energy system directly benefits the residents (i.e., no split incentives), and they can install solar panels by themselves without any complications in their decision-making processes (i.e., no split decision-making).

---

[7] Hereafter, the acronyms in Table 3.1 are used to indicate each group.

Table 3.1 Combined End User Classification of Split Incentives and Split Decision-Making

Category	Tenure	Utility payment	Housing unit type	Related issue
OPS	Owner	Paying	Single-family	No issue
OPM	Owner	Paying	Multifamily	Split decision-making
ONS	Owner	Not paying	Single-family	Split incentives
ONM	Owner	Not paying	Multifamily	Split incentives and split decision-making
RPS	Renter	Paying	Single-family	Split incentives
RPM	Renter	Paying	Multifamily	Split incentives and potential split decision-making
RNS	Renter	Not paying	Single-family	Incentives can be reduced
RNM	Renter	Not paying	Multifamily	Incentives can be reduced and potential split decision-making

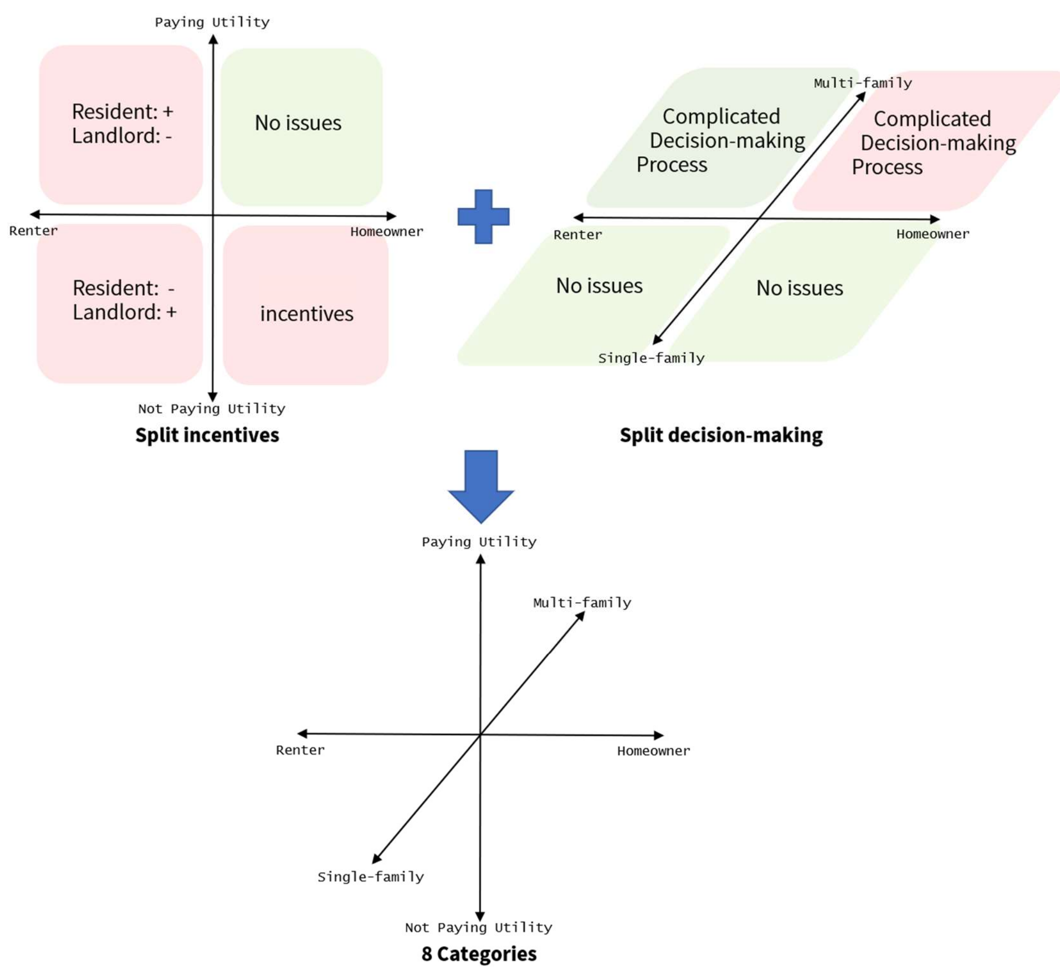


Figure 3.1 Conceptual Visualization of Analytic Framework

In RNS (renter-occupied, not paying for utilities, and single-family), landlords who pay energy costs are more willing to adopt solar energy systems; at the same time, no property control issue exists. There is potential inefficiency in terms of energy consumption because tenants are still exposed to the temptation to waste energy, and landlords do not have meaningful control over tenants' actions. However, from the perspective of solar energy system installation, no split incentives exist because installation of solar panels directly benefit the landlords who pay utility fees, while the magnitude of incentives can be smaller than in the case of OPS.

Similar to RNS (renter-occupied, not paying for utilities, and single-family), the category RNM (renter-occupied, not paying for utilities, and multi-family) has no split incentive issues but has some chance of being affected by the reduced incentives, and additionally, this category can be influenced by the split decision-making issue when there are multiple owners in a multifamily building. However, it is also possible that split decision-making does not have meaningful effects in RNM if the multifamily building is owned by one agent (e.g., a rental company). In this case, the single owner has enough control over the building to install a solar energy system, and the owner sometimes has a greater ability to manage the institutional and legal tasks that accompany the installation.

There are two categories that are affected by split incentives but irrelevant to split decision-making: ONS (owner-occupied, not paying for utilities, and single-family) and RPS (renter-occupied, paying for utilities, and single-family). Housing units falling into these categories are expected to have a lower probability of solar energy system adoption because of split incentives between the agents, who pay energy costs, and the principal, who pays for the installation of solar energy systems. In particular, owners who do not pay utility bills obtain no direct returns from investments in solar energy systems, and landlords whose renters pay utility bills also have no meaningful financial motivations to spend money on solar energy systems.

In contrast, the category of OPM (owner-occupied, utility-paying, and multi-family) faces only the split decision-making issue, meaning that owners who pay energy costs are willing to install a solar energy system to improve long-term efficiency. However, the complexity of completing the collective decision-making process given residents' diverse interests discourages the actual investment.

Lastly, the remaining categories, ONM (owner-occupied, not paying for utilities, and multi-family) and RPM (renter-occupied, paying for utilities, and multi-family), are subject to both split incentives and split decision-making. In housing units in the former category, residents who own units in a multifamily building do not have incentives to install solar energy systems, and even if they are willing to install, the complexities of the decision-making process hinder adoption. In the case of RPM, a similar split incentive problem exists, that is, landlords do not need to invest in solar energy systems. The split decision-making issue can also arise when multiple landlords own units in an apartment building. However, if a multifamily building is owned by a single agent, the split decision-making issue is invalid. Because these two cases are mixed in RPM, potential split decision-making is assumed.

Given this classification, this study uses an analytic framework that compares subgroups with different statuses regarding split incentives and split decision-making, as shown in Figure 3.2. For instance, OPS and OPM, which have no split incentives, can be selected and compared to reveal the effect of split decision-making. Alternatively, to check for the influence of split incentives while controlling for the effect of split decision-making, RPM and RNM can be used.

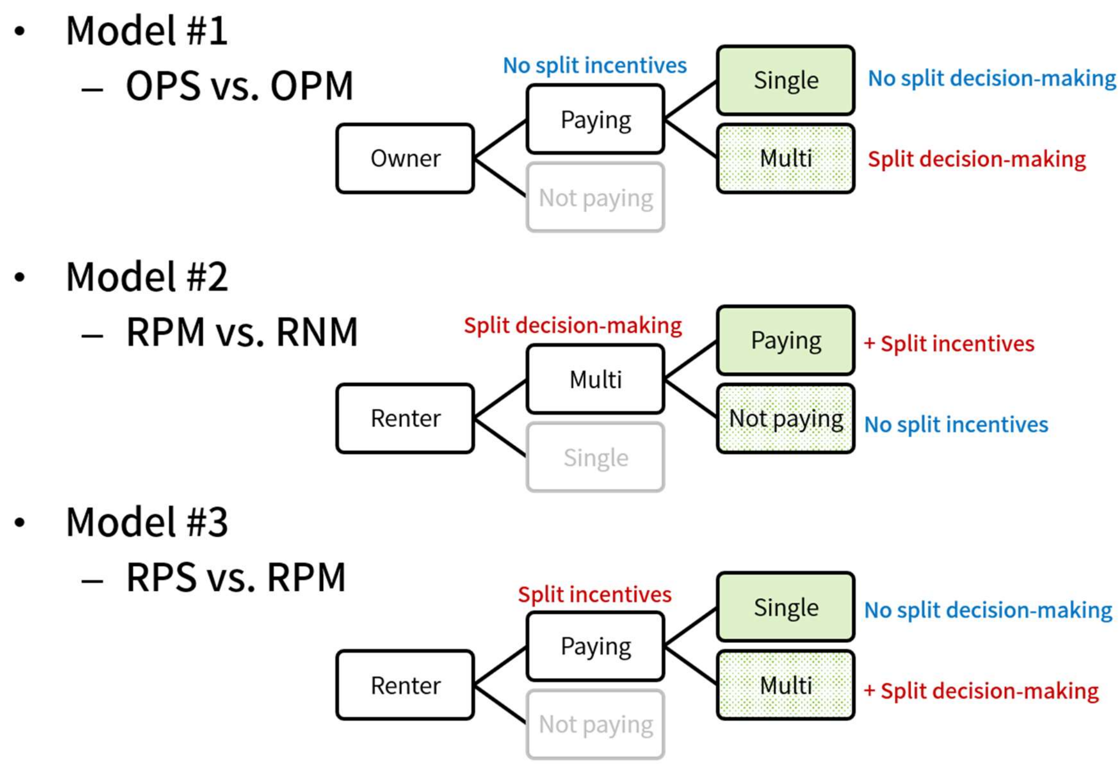


Figure 3.2 Comparison Structure of Models

Additionally, RPS and RPM can reveal differences in solar panel adoption according to different degrees of split decision-making, wherein split incentives commonly exist. This simplified comparison method between each paired category has two fundamental advantages: 1) it can directly reveal the effect of each problem and 2) it offers a greater degree of freedom and can thus better address the issue of small sample size.

Variables. The dependent variables and three key variables are measured in binary form. The use of solar energy (*USESOLAR*) is encoded as 1 if a household uses solar energy for any purpose, including space heating, water heating, and providing electricity for appliances; it is encoded as 0 when a household does not use solar energy.

In regard to the three key variables used to examine the effects of split incentives and split decision-making on the use of solar energy, the *OWN* variable indicates that a housing unit is owned by any of the household's members. If yes, it is encoded as 1, but if the housing unit is occupied by renters, the value is 0. Similarly, *UTILPAY* has a value of 1 when the household living in the dwelling unit pays utility bills themselves, while a value of 0 means the utility bills are paid by other entities (e.g., energy costs are included in rent). *SINGLE* is 1 when a housing unit type is single-family detached or attached, while apartments are encoded as 0 (mobile homes were excluded). It is questionable whether single-family attached dwellings can be considered multifamily housing. However, it seems that such structures are less likely to cause property conflicts because each household generally has shared ownership of the roof. Therefore, this study regards both single-family detached and attached homes as the same category.

To control for the influences of other factors, this study includes several types of control variables that are potentially relevant to solar energy use. Regarding household characteristics, *INC* indicates annual gross household income, and the values are adjusted to 2009 dollars according to the CPI index provided by the U.S. Bureau of Labor Statistics. As for other household characteristics, *HHSIZE* and *ATHOME* are employed. *HHSIZE* is measured as the number of household members living in the dwelling unit at the surveyed timepoint. *ATHOME* is a dummy variable indicating the presence of any household members at home on typical weekdays. In regard to housing unit attributes, housing unit size measured in square feet (*TOTSQFT*) and building age (*BLDAGE*) are used. This study also considers climate factors by employing *CDD* and *HDD*. Additionally, to address locational effects given the limited information in the data, ten dummy variables for each Census Division (*DIVISION1*~

Table 3.2 Descriptive Statistics of RECS

Variables	Description	Mean	S.D.	Min.	Max.
USESOLAR	Dependent variable: indicating the use of solar energy	0.01	0.10	0	1
OWN	Dummy variable: owner-occupied house	0.68	0.47	0	1
SINGLE	Dummy variable: indicating occupants pay the utility bills	0.75	0.43	0	1
UTILPAY	Dummy variable: single-family detached house	0.94	0.24	0	1
INC	Household income in 2009 dollars	49369	37738	1250	142740
HHSIZE	Number of household members	2.66	1.50	1	15
ATHOME	Dummy variable: indicating household members at home on typical weekdays	0.54	0.50	0	6
TOTSQFT	Housing unit size in square feet	2244	1496	100	16122
BLDAGE	Building age in years	24.02	25.35	0	89
HDD	Heating degree days (base temperature 65F)	4206	2222	0	12525
CDD	Cooling degree days (base temperature 65F)	1401	1065	0	5518
RURAL	Dummy variable: indicating a housing unit is located in a rural area	0.18	0.38	0	1

DIVISION10) and a dummy variable for housing located in a rural area (*RURAL*) are included. The descriptive statistics of the variables are reported in Table 3.2.

Data. This study employs data from the RECS in 2001, 2005, and 2009 and the ACS PUMS 5-year estimate for 2011-2015. These surveys provide several advantages over alternative sources of information. The RECS is a comprehensive, multi-year (periodically conducted) survey provided by the U.S. EIA. Its most attractive feature for the purposes of this study is the availability of renewable energy statistics (e.g., those pertaining to the use of solar panels as a secondary energy source), which helps to investigate the adoption of solar energy systems. More specifically, the questionnaire directly asks, “Which of these fuels do you use?” regardless of the purpose (meaning all purposes are included). Out of 19,910 observations, 212 observations are found to use solar energy.

The sample consists of 13,505 owner-occupied and 6,405 renter-occupied housing units, 15,022 single-family and 4,888 multifamily housing units, and 18,683 utility-paying and 1,227 utility-included housing units. In regard to their combinations and the observed cases that use solar energy, OPS has the largest sample size (12,780 housing units) and the highest percentage of solar energy use (189 cases, or 1.48%). OPM has 594 observations, 3 of which are identified as using solar energy (0.51%), and ONS and ONM have 57 and 74 observations, respectively, but there are no housing units with solar energy systems. It is shown that RPS has 2,026 observations, the second largest sample size, but the percentage with solar energy is second-lowest (8 cases, 0.39%). RPM has the lowest percentage with solar energy, at 0.15%, with the exception of zero-percentage categories, which is 5 cases out of 3,283 observations, and RNS has 159 observations, but no solar energy use cases. RNM has the second-highest percentage at 0.75%, or 7 cases out of 939 observations.

Although the RECS provides useful data with which to investigate the effects of split incentives and split decision-making issues on solar energy use, the relatively small sample size (i.e., 19,910 observations across the whole U.S.) and the temporal gap (i.e., from 2001 to 2009, i.e., at least 8 years ago) are caveats. To address this issue, this study attempts to use a larger and more recent dataset to cross-check the validity of the results obtained using RECS. Fortunately, the ACS PUMS meets these criteria. In particular, it provides detailed characteristics of housing units and households, with a large number of observations nationwide. Specifically, after the data cleaning process, the ACS PUMS 5-year estimate 2011-2015 dataset contains 5,985,476 housing unit observations and associated household characteristics.

However, it is evident that these two data sources have some differences, such as their collection methods and focus factors. A major difference is the selection of surveyed elements. More specifically, the RECS considers the use of solar energy for all purposes, including space heating, air conditioning, water heating, cooking, and lighting/appliances. However, the ACS PUMS (hereafter, ACS for the sake of brevity) only includes solar energy use for space heating. Therefore, the overall percentage of solar energy use is much smaller in the ACS, as shown in Table 3.3, and this study presumes that the proportion of the solar energy used for heating fuel in all solar energy uses is uniform.

Table 3.3 Percentages of Solar Energy Use by End User Classifications in RECS and ACS

Tenure	Utility payment	Housing unit type	RECS	ACS
Owner	Paying	Single-family	1.48% (189/12780)	0.08% (3390/4008080)
Owner	Paying	Multifamily	0.51% (3/594)	0.03% (62/184323)
Owner	Not paying	Single-family	0% (0/57)	0.10% (6/6134)
Owner	Not paying	Multifamily	0% (0/74)	0.09% (9/10059)
Renter	Paying	Single-family	0.39% (8/2026)	0.04% (289/721232)
Renter	Paying	Multifamily	0.15% (5/3283)	0.04% (362/887398)
Renter	Not paying	Single-family	0% (0/159)	0.16% (54/34746)
Renter	Not paying	Multifamily	0.75% (7/937)	0.08% (113/133504)
	Total		1.06% (212/19910)	0.07% (4285/5985476)

Results

Estimation results based on the RECS. Using the RECS data, the weighted[8] logistic regression model is conducted, and the results are reported in Table 3.4 in four columns. The first column (model #1), which uses the subsamples of owners and utility-paying housing units, includes *SINGLE* (i.e., OPS vs. OPM) as the key variable. In other words, this model compares the effect of split decision-making (multiple owners) when the split incentives issue does not exist (owners pay utility fees). In contrast, model #2 – by comparing RPM with RNM – examines how split incentives influence solar energy use when there is no split decision-making problem. In model #3, the sample shares attributes of the renter-occupied and utility-paying categories, which raises split incentive issues. However, distinct housing types can yield different degrees of split decision-making. Specifically, RPS and RPM both have split incentives, but RPM is more likely to have split decision-making if there are many owners in a multifamily housing unit. The last model covers all categories that have non-zero solar energy use cases (i.e., OPS, OPM, RPS, RPM, and RNM) and examines the effect of each category.

The results in model #1 indicate that split decision-making has negative effects on solar energy use given that no split incentive issue exists. In the subsamples that are owner-occupied and utility-paying housing units, the estimated coefficient for *SINGLE* is 1.318, suggesting that single-family homes have a higher probability of solar energy use. In other words, owner-occupied multifamily housing units—where a complex decision-making process is required—are

---

[8] Weights on housing unit observations are from the RECS dataset.

Table 3.4 Estimation Results Based on RECS

	Model #1	Model #2	Model #3	Model #4
Intercept	-8.054 ***	7.580	-15.536 ***	-5.298 ***
SINGLE (OPS vs. OPM)	1.318 ***			
UTILPAY (RPM vs. RNM)		-2.595 ***		
SINGLE (RPS vs. RPM)			0.609 **	
OPM				-1.366 ***
RPS				-1.504 ***
RPM				-2.328 ***
RNM				0.295 ***
log(INC)	0.051 *	-0.071	1.178 ***	0.049 *
HHSIZE	-0.128 ***	0.388 ***	-0.303 ***	-0.112 ***
ATHOME	0.166 ***	-1.174 ***	0.498 **	0.098 **
log(TOTSQFT)	0.369 ***	-1.121 ***	0.087	0.256 ***
BLDAGE	0.006 ***	-0.039 ***	0.010 **	0.005 ***
HDD65	-0.0003 ***	-0.0027 ***	-0.0004 ***	-0.0004 ***
CDD65	0.0001 *	-0.0060 ***	-0.0009 ***	-0.0001 ***
RURAL	0.774 ***	-15.969	0.890 ***	0.802 ***
Number of Obs.	13374	4220	5309	19620
McFadden's R^2	0.094	0.456	0.193	0.117

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

less likely to have solar energy systems. When this coefficient is converted to an odds ratio, the ratio is 3.578, meaning that OPS has a more-than-threefold greater probability than OPM of having a split decision-making issue.

Model #2, which uses a subsample of renter-occupied multifamily housing units only, shows that the effect of *UTILPAY* on solar energy use is negative (-2.595). In other words, this indicates that RPM has a lower probability of using solar energy than does RNM, implying the negative impact of split incentives. More specifically, if tenants are paying their energy costs, and thus landlords have less motivation to invest in efficient energy systems, the situation of split incentives hinders the adoption of solar energy systems.

Next, model #3 examines the effect of split decision-making given the existence of split incentives. Model #3 compares RPS and RPM, which have split incentive issues in common but have different degrees of split decision-making. The results indicate a higher probability of solar energy use in RPS (0.609), which has no split decision-making issue. Therefore, this result also confirms the negative effect of split decision-making.

Lastly, model #4 includes all categories with non-zero solar energy use percentages (i.e., excluding ONS, ONM, and RNS) to enable a more comprehensive comparison. Table 3.5 summarizes the results, and it is found that RNM has the highest coefficient, followed by OPS (reference group). RNM has split decision-making problems when there are multiple landlords in a building, and hence it is expected to have a lower value than OPS, which has neither split incentives nor split decision-making. However, this unexpected result is probably due to two factors. First, in the U.S. context, most multifamily housing units are owned by companies, so split decision-making is less influential in renter-occupied multifamily housing units. Second, compared with individual owners, companies usually have more professional resources, such as lawyers, financial managers and planners. In other words, companies face relatively lower costs when addressing legal and institutional processes than do individuals, and consequently they are more likely to implement solar energy systems. After OPS, the third rank is assigned to OPM, which is characterized by split decision-making but no split incentives. The second-lowest is RPS, which has split incentives only, and the lowest coefficient is found for RPM (-2.328), which has both split incentive and split decision-making (if landlords are individuals) issues. This rank order is consistent with the expectation of this study that having split incentives or split decision-making hinders solar energy system adoption. The result (in particular, the lower

Table 3.5 Existence of Split Problems and Corresponding Coefficients by Category (RECS)

Category	Split incentives	Split decision-making	Coefficient
OPS	No	No	Reference
OPM	No	Yes	-1.366
RPS	Yes	No	-1.504
RPM	Yes	Partial	-2.328
RNM	No	Partial	0.295

coefficients of RPS and RPM compared to OPM) also implies that split incentives have more negative effects on solar energy system adoption than does split decision-making.

For household characteristics, the effects are consistent across the models, with the exception of model #2, probably because all observations in model #2 are renter-occupied multifamily housing units, which have some unique correlations and patterns. So, the explanation here generally pertains to models #1, #3, and #4, while model #2 is discussed later. The coefficients for household income are positive. This is consistent with the findings of previous studies, such as Komatsu et al. (2011) and Kwan (2012), that disposable income plays an important role in solar energy system installation. Solar energy systems are able to save energy costs in the long run, however, installation requires a high initial investment, and break-even usually takes more than a year unless there are incentive programs in place. In this sense, higher household income is likely to allow room in the household budget for solar energy system installation, while households with small amounts of disposable income cannot afford to install such systems.

The negative effect of *HHSIZE* and the positive effect of *ATHOME* can also be explained when consideration is given to the varying expenditure patterns and/or lifestyles of different groups of households. All else being equal (including income and the total amount of energy use), a larger household, such as a family with multiple children, may need to spend its income on various other needs, as opposed to making a one-time investment in an advanced building energy system. In contrast, households with a person who stays home on weekdays (i.e., *ATHOME*=1) may have a higher adoption rate than those without such a household member, as they may be able to handle the installation process, and/or they may be exposed to information or incentives related to new systems. Additionally, residents who are at home are better able to install solar panels by themselves, and at much lower costs, which in turn has positive impacts.

Explanatory variables about housing unit attributes are all positive and significant, which is consistent with expectations. A positive coefficient for *log(TOTSQFT)* suggests that larger housing units are more likely to use solar energy because there is more space to install solar panels. The ages of residential buildings have positive impacts, which goes against general expectations that newly built homes are more receptive to the installation of solar energy systems. However, old buildings provide opportunities for renovations, and residents can install a solar energy system as part of other retrofits. Based on the given sample, it is suggested that older buildings have a higher probability of using solar energy, even though the effect is small.

Regarding locational variables, homes in rural areas are found to have a higher probability of solar energy use. This can be explained by the same reasoning as that underlying the relationship between housing size and solar energy use, namely that having a greater amount of available land might allow solar panel installation. Climate variables showed all negative influences except model #1, and the magnitude of *HDD* was much greater than that of *CDD*. Considering that these two climate variables have a high negative correlation, the result may imply that housing units in hot regions (where *CDD* is high) are more likely to use solar energy systems, presumably due to a higher level of solar energy productivity from abundant sunlight.

In regard to the exceptional case, model #2, all control variables show contrasting effects compared to the other models, with the exceptions of *HDD* and *CDD*, but household income and *RURAL* do not reach statistical significance. As mentioned above, these reversed results may be due to the uniqueness of the renter-occupied multifamily category, and hence the mechanism of solar energy adoption may be totally different. Regarding housing unit characteristics, smaller and newer units tend to have solar energy systems. However, here, “smaller” refers to the size of a single unit in an apartment and thus needs to be interpreted carefully. In regard to household characteristics, larger households and households that do not have any household members at home on weekdays are positively related to solar energy use. However, it seems too early to make conclusive interpretations of these different findings. First, more in-depth studies focusing on multifamily housing units are required.

One additional notable estimation result concerns the coefficients of regional dummy variables included to control for the interregional variation in adoption rates, and these values are reported in Table 3.6 and visualized in Figure 3.3. Taking the West North Central division as the reference category, the highest positive effect is observed in New England, followed by the Mountain North, Pacific, and Mountain South divisions, which are mainly blue states. Meanwhile, the lowest value is found in East South Central, and the second lowest in West South Central, which are mainly red states. This finding appears to be in line with some recent studies indicating a significant difference between liberals and conservatives in terms of their support for smart growth and other remedies for global warming (see, e.g., McCright and Dunlap, 2011; Weber and Stern, 2011; Lewis, 2015). Additionally, the range of the regional dummy variables (from -2.70 to 1.22) is as wide as the range of the category dummy variables in model #4 (from -

2.33 to 0.30), implying the importance of regional characteristics. However, a more rigorous investigation is needed to ensure a precise interpretation of these results.

Estimation results using the ACS. This study further investigates the effects of split incentives and split decision-making on solar energy system adoption using a more recent and larger data set, the ACS. However, it should be noted that some variables included in the previous estimation model, which used RECS, are not available in the ACS, and hence the control variable set is modified to a common variable set. More specifically, housing size, which does not exist in the ACS, is changed to number of rooms. Additionally, the HDD, CDD and rural area dummy variables are removed.

Using a weighted logistic regression model, the estimation results with different data sources show identical directions of split incentives and split decision-making, as summarized in Table 3.7. Although the magnitudes vary, it is again found that OPM with the split decision-

Table 3.6 Estimated Fixed Effects by Census Division based on RECS

Census Division	Description	Fixed effect
1	New England Census Division (CT, MA, ME, NH, RI, VT)	1.22
2	Middle Atlantic Census Division (NJ, NY, PA)	-0.96
3	East North Central Census Division (IL, IN, MI, OH, WI)	0.06
4	West North Central Census Division (IA, KS, MN, MO, ND, NE, SD)	0 (Ref.)
5	South Atlantic Census Division (DC, DE, FL, GA, MD, NC, SC, VA, WV)	-1.20
6	East South Central Census Division (AL, KY, MS, TN)	-2.70
7	West South Central Census Division (AR, LA, OK, TX)	-1.83
8	Mountain North Sub-Division (CO, ID, MT, UT, WY)	0.61
9	Mountain South Sub-Division (AZ, NM, NV)	0.27
10	Pacific Census Division (AK, CA, HI, OR, WA)	0.52

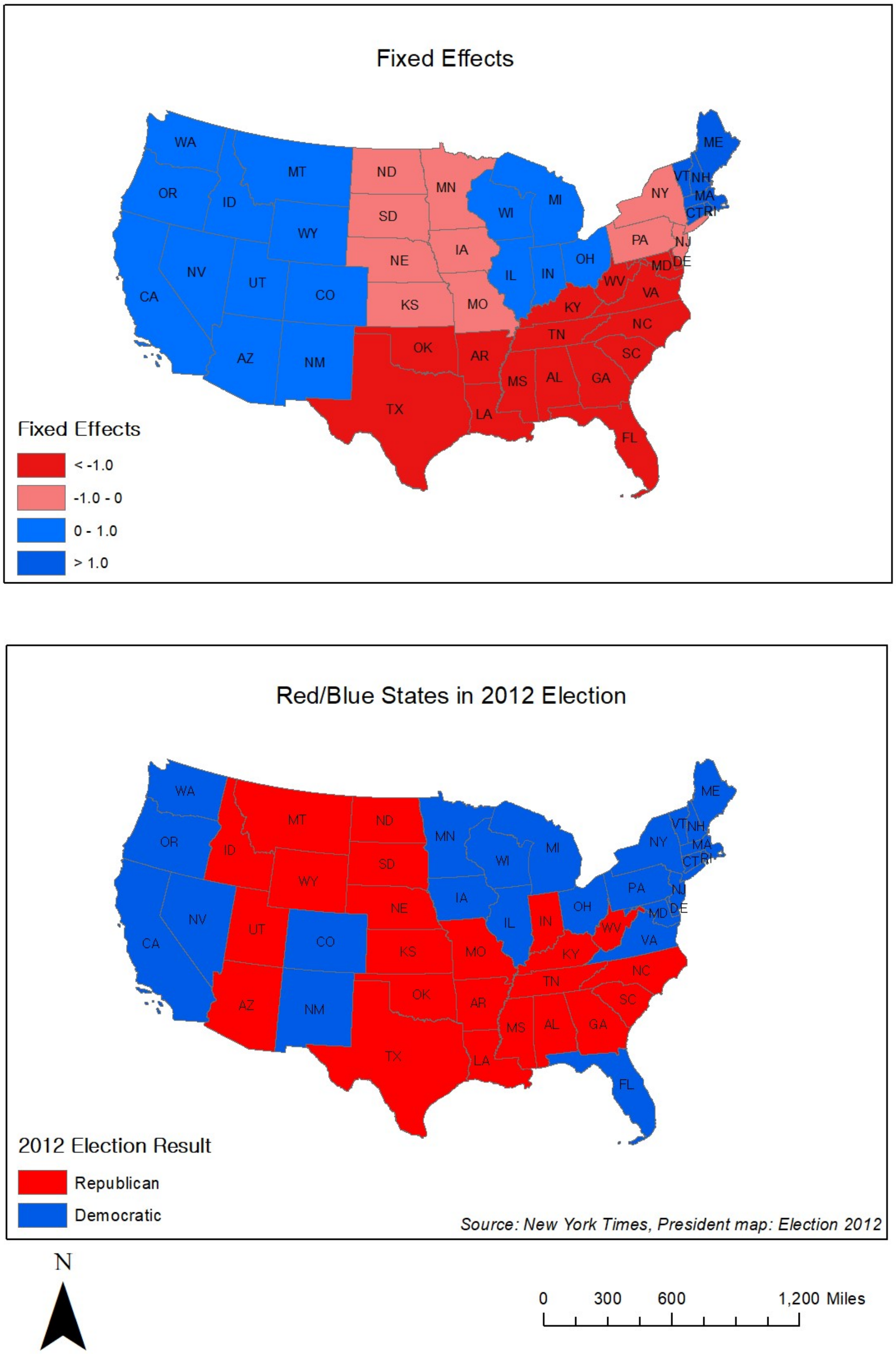


Figure 3.3 Comparing Patterns of Fixed Effects and Political Inclinations

making issue has a lower probability of solar energy use than does OPS. Similarly, RPM with split incentives and RPM with both split incentives and split decision-making are less likely to have solar energy systems than are RNM and RPS, respectively.

However, control variables show different effects between RECS and ACS, but ACS itself presents a reasonable pattern. That is, models #2 and #3 have the same patterns of control variables. Specifically, in these two models, household income, household size, and building age have negative impacts on solar energy system adoption, whereas the presence of household members at home on weekdays, as well as total number of rooms, have a positive influence. However, model #1 shows the positive impacts of household income and household size. The clear difference between model #1 and the other models (#2 and #3) is tenure status. That is, model #1 is based on owner-occupied housing units, while #2 and #3 are renter-occupied housing units. This implies that there are distinct mechanisms of solar energy system adoption depending on tenure status and that income and household size, in particular, play more positive roles in owner-occupied housing units.

A comprehensive model that uses all available categories in RECS is also conducted and compared to the other models. Model #4 in Table 3.7 presents the estimated coefficients, and it is found that the directions of all variables are identical. Both models have RNM and OPS (the reference group) in first and second place, with non-negative effects. However, RPS, RPM, and RNM show different orders between the two models, as shown in Table 3.8. This difference is probably due to distinct variable definitions of ACS, especially regarding solar energy use; or, the temporal gap between RECS (i.e., 2001-2009) and ACS (i.e., 2011-2015) may yield this difference. However, from a broader perspective, it is common for split incentives and split decision-making issues to negatively influence solar energy system adoption.

Table 3.7 Comparison of Estimation Results between RECS and ACS

	Model #1		Model #2		Model #3		Model #4 (Ref. OPS)	
	RECS	ACS	RECS	ACS	RECS	ACS	RECS	ACS
Intercept	-7.382 ***	-12.077 ***	-18.372	-4.988 ***	-18.837 ***	-6.612 ***	-5.733 ***	-9.439 ***
SINGLE (OPS vs. OPM)	1.392 ***	1.061 ***						
UTILPAY (RPM vs. RNM)			-2.353 ***	-0.749 ***				
SINGLE (RPS vs. RPM)					0.389 *	0.148 ***		
OPM							-1.397 ***	-1.061 ***
RPS							-1.482 ***	-0.835 ***
RPM							-2.370 ***	-0.810 ***
RNM							0.100	0.152 ***
log(INC)	0.075 ***	0.350 ***	-0.188 **	-0.182 ***	1.158 ***	-0.077 ***	0.057 **	0.217 ***
HHSIZE	-0.145 ***	0.008 ***	0.413 ***	-0.036 ***	-0.379 ***	-0.029 ***	-0.126 ***	0.005 *
ATHOME	0.222 ***	0.196 ***	-1.071 ***	0.169 ***	0.469 **	0.197 ***	0.137 ***	0.179 ***
log(TOTROOM)	0.093 ***	0.013 ***	-0.429 ***	0.061 ***	0.214 ***	0.025 ***	0.085 ***	0.028 ***
BLDAGE	0.003 **	-0.016 ***	-0.032 ***	-0.012 ***	0.012 ***	-0.017 ***	0.002 **	-0.016 ***
Number of Obs.	13374	4192403	4220	1020902	5309	1608630	19620	5934537
McFadden's R^2	0.070	0.093	0.303	0.036	0.179	0.036	0.096	0.084

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Table 3.8 Comparison of Split Incentive and Split Decision-making Problems

Category	Split incentives	Split decision-making	Coefficient (rank): RECS	Coefficient (rank): ACS
OPS	No	No	Reference (1)	Reference (2)
OPM	No	Yes	-1.397 (3)	-1.061 (5)
RPS	Yes	No	-1.481 (4)	-0.835 (4)
RPM	Yes	Partial	-2.370 (5)	-0.810 (3)
RNM	Partial	Partial	0.100[a] (1)	0.152 (1)

[a] Not statistically significant at the 10% level

Conclusion

This study highlights the complexity of energy-related choices caused by inter-agent dynamics, with an explicit focus on the adoption of solar energy systems in residential buildings. Although individuals behave rationally, their complicated incentive structures and decision-making processes, which take on different forms depending on various contextual structures, sometimes yield socially inefficient outcomes. Regarding solar energy adoption, this study views two contextual conditions, split incentives and split decision-making – both of which are shaped by ownership structure, utility payment status, and housing unit type – as potential barriers to the promotion of solar energy installation.

Using two national datasets, the RECS and ACS, the results of logistic regression show that both split incentives and split decision-making significantly discourage the adoption of solar energy systems, and these findings are consistent with earlier studies (Murtishaw and Sathaye, 2006; Gillingham et al., 2012; Puustinen and Viitanen, 2015). Specifically, renter-occupied dwelling units where tenants pay utility bills, which are affected by the split incentive issue, and owner-occupied multifamily dwelling units, which are affected by the split decision-making issue, have significant negative impacts on solar energy adoption. However, renter-occupied multifamily housing units where tenants pay energy costs have a similar or higher probability of solar energy adoption than the reference category (owner-occupied, utility-paying, and single-family), where neither split incentives nor split decision-making exist, presumably because when a building is owned by a single entity, such as a rental corporation, the split decision-making issue is not valid, and furthermore, the company-level owner usually has better financial and institutional abilities to install solar panels. Although some of the effects vary by subsamples or data sources, it is consistently found that split incentives and split decision-making are detrimental to solar energy system adoption. Regarding the effects of socio-economic factors, both household income and the presence of household members at home on weekdays are positively related to solar energy system adoption. This implies that changing to a solar energy system still requires considerable financial and informational resources. On the other hand, number of household members, number of HDD, and number of CDD are negatively associated with the adoption of solar energy systems.

The findings of this study can explain why the adoption of renewable energy, including solar energy, is extremely low despite the many subsidies and incentives provided by governments. That is, while financial supports encourage such adoptions, split incentives and complications in the decision-making process can distort incentive-based mechanisms. To cope with these issues, policy-makers can consider several approaches. Regarding split incentives, which occur when residents are not charged for their energy consumption, it should be highlighted that this issue is related to energy use metering at the level of individual dwelling units (Levinson and Niemann, 2004). Therefore, incentive policies for installing individual meters and regulative policies on utility-included rental units are possible approaches to alleviating the inefficiencies generated by split incentive problems.

Additionally, the results suggest that the adoption of solar energy systems involves not only economic incentives but also behavioral and social issues, especially in regard to managing the conflicting interests of different agents. In fact, the crux of the problem is that people behave very economically rationally at the individual level instead of behaving in a way that maximizes utility for society as a whole. In this sense, interdisciplinary approaches that can promote efficient communication, negotiations, and collective decision-making among agents are recommended to overcome social and institutional hurdles on the way to more active adoption of solar energy systems.

Despite the significant detrimental effects of misaligned incentives and complications in the decision-making process on the adoption of solar energy systems, the importance of governments is also implied by the results of this study. In other words, the willingness and efforts of governments – especially at the state and local level – to encourage the adoption of solar energy systems is obviously a major driving force. Additionally, this is further related to topic about the effects of governance structure on resource management (see e.g., Kim et al., 2015), particularly, whether political fragmentation tend to encourage solar energy system adoption. In this sense, it is suggested that future studies comprehensively consider both inter-agent complications and a variety of renewable energy policies within the context of government institutions.

Unfortunately, recent attempts to significantly cut budgets for renewable energy incentives and for research and development programs, as well as decisions to increase tariffs on solar panels to protect the domestic economy, are moving in the opposite direction from the dispersion of renewable energy, including solar energy (Mufson and Mooney, 2018; Swanson and Plumer, 2018). However, it is also true that the cost of solar energy is rapidly falling, from

52 cents per kWh in 2010 to 15 cents per kWh in 2017, making solar energy systems more attractive (Cook et al., 2018). Presumably, in the future, solar energy installation is less likely to be affected by incentive programs, and hence, policies on solar energy installation are likely to have smaller effects. However, split incentive and split decision-making issues still exist regardless of economic feasibility. Therefore, we need to invest greater effort in adjusting these systemic inter-agent misalignments, and if we successfully do so, our efforts will contribute to developing a society based on more sustainable energy systems.

CHAPTER 4

Urban Form and Residential Energy Consumption:

Exploring the Seasonal Variation of This Relationship in Chicago

Introduction

Growing concerns about global climate change and other environmental consequences associated with high energy consumption have led to renewed interest in energy issues and have motivated attempts to address related challenges in many disciplines. Urban planners, among others, have paid considerable attention to 'urban form' as a key determinant of energy use and thus as a possible way to improve or modify built environments to reduce energy consumption. Specifically, over the past several decades, numerous studies have investigated the relationship between urban form and transportation energy consumption and have reported that denser urban structures can lead to shorter travel distances, thus promoting transportation energy savings (see, e.g., Newman and Kenworthy, 1989; Cervero and Kockelman, 1997; Brownstone and Golob, 2009).

Recently, scholars have suggested that energy consumption in residential sectors is strongly associated with the way we design and develop our cities. However, there has been relatively little research on the relationship between urban form and residential energy consumption (Ko, 2013). Consequently, little is known about the complex mechanisms through which changes in urban form increase or decrease energy use in residential sectors. Furthermore, there are competing views in the literature regarding what constitutes a so-called 'energy efficient urban form' in terms of residential energy consumption. On the one hand, it has been argued that a more compact urban form can result in a higher level of efficiency (Stone, 2006). On the other hand, such high-density development is often viewed as inefficient given that it can lead to an increase in local temperatures due to reflected heat from paved surfaces, which prompts residents to consume more cooling energy (Taha et al., 1988). In addition to density, detailed land-use/land-cover patterns have been assumed to have a significant impact on residential energy use by altering microclimates or thermal transmission mechanisms, but their exact impacts have remained unclear and thus require more research.

Given the lack of consensus, this study aims to expand knowledge about how various dimensions of urban forms are associated with residential energy consumption. To achieve this aim, this study performs a detailed analysis of residential building energy consumption, including an analysis of energy consumption patterns in the city of Chicago, where a substantial degree of heterogeneity exists across neighborhoods in terms of density, land-use patterns, and other important dimensions of urban form. One major highlight of this study is its exploration of how the influence of urban form on residential energy consumption varies by seasons with distinct climate conditions. This task is accomplished by taking advantage of detailed energy use data that include monthly information. In this way, this study is expected to contribute to a more comprehensive understanding of the energy implications of urban design, development, and planning.

Literature on the Nexus between Urban Form and Residential Energy Consumption

Although the relationship between urban form and energy consumption has been investigated by scholars for decades, relatively little attention has been paid to the relationship between urban form and residential versus transportation energy consumption. Scholars often view residential energy consumption from economic and/or behavioral perspectives that focus on individual households' choice mechanisms, but these approaches do not provide meaningful insights for planners who must address physical urban spaces. Recently, however, there has been increasing interest in understanding how urban forms influence residential energy consumption by considering a variety of urban forms and contexts.

Density is one of the most conventional and frequently mentioned aspects of urban form. This variable is sometimes presented in different yet relevant forms, such as compactness or urban sprawl. Higher density is generally perceived to be associated with a greater proportion of multifamily housing and/or smaller dwelling units that have shapes with less exposure to outdoor climates (e.g., through the windows and roof); therefore, denser urban structures lead to lower per capita residential energy consumption. Numerous empirical studies have examined this effect of density and suggested the presence of energy-saving benefits from higher densities, especially with regard to heating energy demands. For instance, using data from the RECS 2005 on three counties in Illinois, Wilson (2013) reports that density is negatively associated with summer electricity use, whereas the winter electricity usage model showed no statistical significance. Studies that use detailed urban morphologies have also reached similar conclusions. Focusing on the four largest European cities (i.e., Paris, London, Berlin, and Istanbul), Rode et al. (2014) show that neighborhoods with higher densities or taller buildings were the most heat-energy efficient, whereas areas mainly consisting of detached housing types are the least energy efficient. Other studies using similar approaches but different geographical contexts find that denser urban forms are positively associated with energy efficiency, although climate can change the strength of the relationship, as seen, for example, in the U.S. (Quan et al., 2014), China

(Quan et al., 2016) and Greece (Vartholomaios, 2017). However, some proxies for density provide consistent results with respect to the proportion of multifamily housing units (Kaza, 2010) and the urban sprawl index (Ewing and Rong, 2008), although they find meaningful benefits only for heating energy demands.

In contrast, some argue that higher density can increase the demand for energy, especially because the presence of more paved surfaces results in a stronger urban heat island effect (Taha et al. 1988). The urban heat island effect is viewed as a factor that increases summer energy consumption but decreases winter energy consumption. For example, Ewing and Rong (2008) find that a greater degree of urban sprawl is related to increased use of cooling energy. However, contrary to the conventional perception, some scholars argue that areas with lower density can exhibit higher degrees of the urban heat island effect for two reasons: 1) the large proportion of un-canopied suburban areas (Stone and Rodgers, 2001; Stone and Norman, 2006); and 2) the much larger lot sizes per household in suburban areas, although heat emissions per building area are lower than in dense areas (Ko, 2013). Additionally, some studies note other detrimental impacts of dense urban forms, such as reduced solar exposure and poor air flow, especially in narrower streets and/or in more shaded areas (Ko, 2013; Urquizo et al., 2017). It is not empirically clear, however, that the relative losses from higher density are significantly greater than the corresponding benefits.

In analyzing residential and building energy consumption, some studies using simulations or experimental methodologies have included building or neighborhood design factors in addition to urban forms. For example, Quan et al. (2014 and 2016) and Rode et al. (2014) investigate the effects of the floor-to-area ratio on building energy consumption, and Steadman et al. (2014) and Vartholomaios (2017) consider the ratio between building volume and the exposed surface area of the building. Additionally, the role of building orientations is highlighted and examined by Ko (2013), Delmastro et al. (2015), and Hemsath (2016). These studies reveal that design elements have valid effects on energy consumption. Specifically, a lower aspect ratio (i.e., a greater street width and/or a lower building height) provides greater solar accessibility and better natural ventilation, and streets laid from east to south expose homes to more sunlight, resulting in less residential energy consumption.

Although land-use diversity is considered a crucial element in transportation energy (e.g., Cervero and Kockelman, 1997), few studies have examined residential energy and land-use diversity. Wilson (2013) examines the residential electricity consumption of single-family homes in Illinois using an edge contrast metric that captures the extent of dissimilarity between subdivisions and adjacent land uses. The author hypothesizes that a higher degree of edge contrast has a positive impact on electricity consumption, which is caused by the absence of windbreak or thermal emission benefits in the winter; the results report greater energy uses in winter.

Increasing the amount of vegetation (e.g., trees) in urban areas has also attracted interest as a way to reduce energy consumption by reducing extreme sunlight during the summer and keeping buildings warmer during winter (Huang et al., 1987). According to Ko (2013), trees significantly affect energy consumption by reducing energy use, but they must be properly chosen and placed in the right locations according to crown types, growth speed, and expected shading and windbreak effects. This argument is buttressed by an empirical study that used detailed urban form variables with LiDAR (Light Detection and Ranging) data in Sacramento, California (Ko and Radke, 2014). The authors find that for a parcel with dense green space within a 100-foot radius, a greater accumulated tree height within 60 feet on the east, west, and south sides involved less cooling energy consumption. Although similar findings are established in many other empirical studies (e.g., McPherson and Simpson, 2003; Calceranoa and Artinelli, 2016), contradictory arguments assert that trees can increase energy use if imprudently planted in a manner that, for example, blocks sunlight or hinders natural ventilation (Laveme and Lewis, 1995).

The literature shows that various elements of urban form are strongly associated with residential energy use. Although the current literature provides useful insights, there is contextual variance in the relationship between urban form and residential energy consumption. As Ko (2013) noted, "Due to the complex trade-offs across urban forms and climates, it is unlikely that one urban form is universally ideal" (p. 341). The previous literature has paid less attention to this complexity, and therefore a more comprehensive understanding of the diverse effects of urban forms on energy consumption – as a result of environmental factors – is warranted. To address this knowledge gap, this study attempts to explore how the association between urban forms and residential energy consumption in an urban area varies by season, controlling for other confounding variables and spatial autocorrelation.

Data and Methodology

The present study focuses on the city of Chicago, Illinois, which is the third-largest city in the United States and has a population of 2.7 million. Chicago provides a good opportunity to examine the relationship between urban form and residential energy use because its development pattern varies widely from the core area, which has many high-story buildings, to the periphery, which has a much lower density and distinct land-use pattern. The city also exhibits large climate variation and thus allows for the investigation of how a certain form of urban development is associated with energy consumption under various climatic conditions across seasons. Specifically, in 2010, the temperature in Chicago ranged from -1°F to 94°F, and HDD and CDD for a base temperature of 65°F were 6,247 and 1,028, respectively. For comparison, the temperature in Los Angeles, California ranged from 39°F to 105°F, with 1,359 HDD and 346 CDD. Another advantage of choosing Chicago for this study is the availability of data, that is, the 2010 Energy Usage dataset that contains monthly energy usage statistics for 66,974 residential, commercial, and industrial buildings throughout the city. This study utilizes data for 48,881 residential buildings located within the city, and the monthly energy usage information is aggregated into a block group level using the census block code available in the dataset.

Based on the monthly energy usage information, this study generates six dependent variables. The first four variables are based on amounts of energy use in kBTU[9] (i.e., average monthly energy consumption per housing unit) and are associated with different time periods as follows: (1) the entire year; (2) non-extreme weather seasons (April, May, June, October, and November); (3) summer (July-September); and (4) winter (December-March). These measurements can reveal the degree to which changes in urban forms increase/decrease residential energy consumption in the study area.

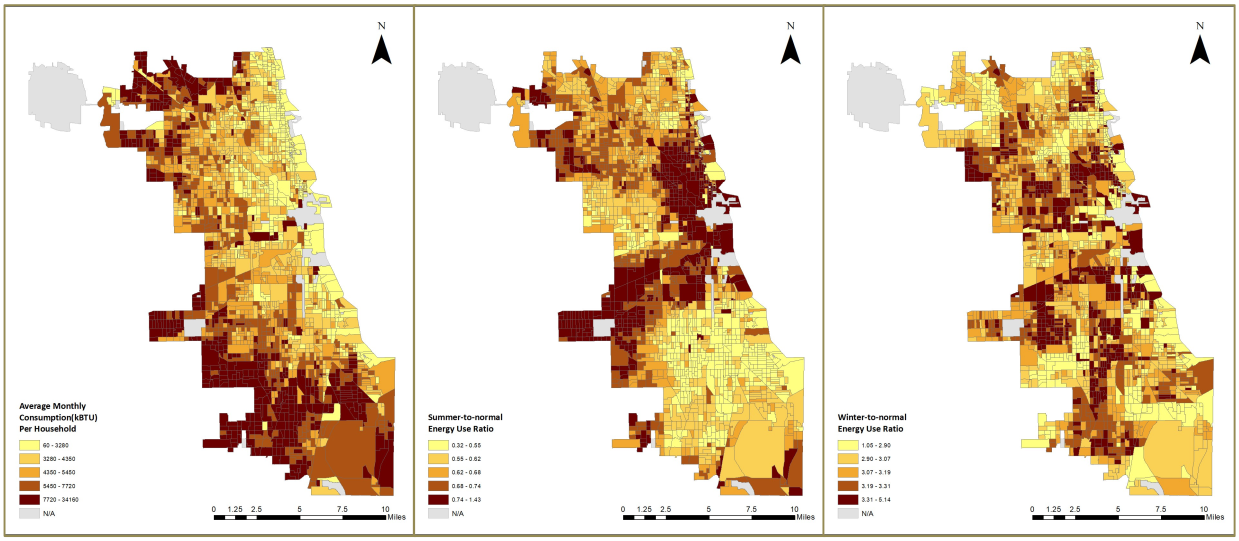
However, this approach has a limitation. Although the results using these amount-based variables may show different estimates across seasons, the estimates may be biased toward observations with larger energy consumption because a higher weight is placed on those

[9] The conversion rates are 1 kwh = 3.41 kBTU and 1 therm = 99.98 kBTU.

estimates. For example, assuming there are two areas, one using 1,000 kBTU/month and the other using 200 kBTU/month, the former area will show greater differences in the amount consumed than will the latter area, with both areas having the same percentage change (e.g., a 100% increase for each area yields 2,000 kBTU/month and 400 kBTU/month, respectively). To address this scaling issue, this study includes two additional measures based on the ratio between seasons: (5) the ratio of summer-season to normal-season energy consumption; and (6) the ratio of winter-season to normal-season energy consumption. By using the ratio variables, different energy consumption scales among block groups can be standardized. In addition, this method can better control for unobserved variables, which are not significantly related to seasonality.

In Figure 4.1, three energy consumption patterns (models #1, #5, and #6, respectively) are presented. The average monthly housing unit energy usage of the entire year indicates that the eastern areas, including the shore of Lake Michigan, have a lower level of energy consumption (kBTU/(housing unit × month)), whereas the southern and northwestern parts of the city exhibit relatively higher levels of energy usage. With regard to energy consumption ratios among seasons, the summer-to-normal ratio is high along the canal, probably because of the effects of that particular environment, such as humidity, paved land, and air pollution from nearby industrial or public facility land uses. Conversely, the winter-to-normal ratio does not show a strong pattern.

This study employs multiple elements of urban form as key variables in order to examine their impacts on residential energy consumption. Specifically, the following six elements are measured: population density, road network density, edge contrast, average number of stories of buildings, average percentage of impervious area, and average vegetation index. Each of the measures is designed to capture an important aspect of physical urban form that can make a



(a) (b) (c)

Figure 4.1 Energy Consumption (kBTU) Per Household:
(a) Annual Average, (b) Summer-to-Normal Ratio, (c) Winter-to-Normal Ratio

meaningful difference in residential energy consumption in urban areas. For instance, urban areas with plentiful trees tend to have lower temperatures as a result of shade and plant evaporation; therefore, these areas' cooling energy demands in summer can be smaller. In contrast, urban areas with more paved surfaces are more likely to demand greater cooling energy because of heat emissions from tarmac, the so-called urban heat island effect. Table 4.1 presents the definition of each urban form variable and its associated hypothesis.

Additional information for the explanatory variables is obtained from the Decennial Census of 2010, the ACS 5-year estimate 2009-2013, and the Smart Location Database as block group-level data. Household income is the one of the strongest economic variables and determines the consumption levels of various resources (including energy). It is well known that affluent households consume more energy. Household income is represented by a median household income variable at the block group level. However, another critical economic variable, price, is not included in the model because Chicago has a single utility provider for electricity (ComEd) and natural gas (Peoples Gas). Although tariffs may vary by contract, the variation in the average price is negligible in the study area. Following Shin's (1985) finding that consumers are more responsive to the average energy price of their utility bill than to the corresponding marginal price, this study assumes that there are no meaningful variations in the price effect.

Although educational attainment usually exhibits a high correlation with income, higher educational attainment is also associated with more opportunities to develop environmental knowledge that leads to pro-environmental attitudes. In this study, the percentage of people holding a bachelor's degree or higher in the over-25 population is included to control for the effects of education, and this variable is expected to have a negative relationship with energy consumption because higher educational attainments are found to increase environmental knowledge and concern (Clery and Rhead, 2013). Although the direction may not be clear, housing tenure status is also an important factor to consider. Renter-occupied homes tend to exhibit higher energy use if utility fees are included in rents, although renters have limited appliance choices and are restricted in increasing their energy consumption. For this reason, the percentage of renter-occupied homes in a block group is included.

We also consider demographic variables that have potential relationships with energy use. The number of household members is generally assumed to increase home energy consumption, and this study employs average household size in a block group. Populations that are physically vulnerable to hot and cold weather, such as the elderly and young children, are also considered. In particular, the percentage of the population over 65 years of age and the percentage of the population under 6 years of age are encoded as demographic variables.

Table 4.1 Description and Formula for Urban Form Variables

Urban form variable	Definition	Description
Population density	$\frac{Total\ population}{Total\ unprotected\ land\ area}$	Population density: Higher population density usually comes with smaller lot sizes and dominance of multifamily dwellings that have better insulation (Ko, 2013). The expected direction is negative.
Road network density	$\frac{Total\ road\ length}{Total\ land\ area}$	Roads create block boundaries and allow more sunlight and wind flow in open spaces. These roads can help energy conservation by providing spaces with natural lighting and ventilation. However, high road density is also related to noise and air pollution generated by traffic on roads, which may cause residents to close their windows (depending on air conditioning) during the summer. In addition, wind flows along road networks increase the demand for heating in winter.
Edge contrast	$\frac{\sum Boundary_i * contrast_{k,l}}{\sum Boundary_i}$ Note: k and l indicate different land uses adjacent to boundary segment i	Edge contrast has been found to increase winter energy consumption among single-family homes in Illinois (Wilson, 2013). It is notable that the city of Chicago is mostly covered by developed land-uses and some watersheds (the lake and canals), and a higher edge contrast is generally correlated with the existence of watersheds. Therefore, an increase in summer energy consumption with higher edge contrast is assumed because proximity to a watershed increases humidity. The expected direction is positive.
Average number of stories of buildings	$\frac{Total\ building\ stories}{Total\ number\ of\ buildings}$	Skyscrapers generate wind-roads during the winter that result in greater demand for heating. In addition, higher buildings are more likely to have worse natural ventilation, and hence space-cooling energy increases in the summer. Therefore, the expected direction is positive.
Average percentage of impervious area	$\frac{\sum Impervious\ \%\ of\ cell_i}{Total\ number\ of\ cells}$	As more surfaces are paved, the urban heat island effect becomes stronger (Stone and Rodgers, 2001). This significantly increases energy use in summer and may have an influence on energy use in winter. The expected direction is positive or neutral.
Average Normalized difference vegetation index (NDVI)	$\frac{\sum Total\ NDVI\ of\ cell_i * Land\ area_i}{Total\ land\ area}$	Vegetation covers decrease albedo and emit heat through the transpiration process. Empirically, there is substantial evidence of temperature reduction by vegetation during summer (Ko, 2013; Ko and Radke, 2014). However, evergreen plants can break winds in winter.

Regarding housing unit characteristics, the percentage of single-family detached housing units in a block group is used to control for the effects of housing types. Because single-family detached homes have more areas that are sensitive to outdoor climates (e.g., windows, roofs, and walls), this variable is expected to have a positive effect on energy use. The building age of the housing unit is another factor associated with energy consumption and is included in the estimation model as the average building age of a block group. However, this linear relationship is not clear because old buildings have a higher probability of being retrofitted. The list of variables, data sources, and descriptive statistics is presented in Table 4.2.

Table 4.2 Variables, Descriptive Statistics, and Data Sources

Variable	Mean	S.D.	Median	Data Source
Total BTU	5,530.16	3,077.17	4,876.50	EU[a], DC[b]
Normal Season BTU	3,370.46	1,900.40	2,961.39	EU, DC
Summer BTU	2,164.09	1,283.71	1,850.92	EU, DC
Winter BTU	10,443.64	5,764.44	9,332.43	EU, DC
Summer-to-normal ratio	0.65	0.12	0.65	EU, DC
Winter-to-normal ratio	3.1	0.28	3.13	EU, DC
Population density	33.37	27.69	27.34	SLD[c]
Road density	23.27	6.15	23.06	SLD
Edge contrast	1.02	2.86	0.00	NLCD
Average building stories	1.92	1.45	1.70	EU
Average impervious area	65.95	12.87	67.00	NLCD[d]
Vegetation (NDVI)	44.90	4.51	44.50	AVHRR[e]
Median income	49,790	27,182	43,790	ACS[f]
High education %	0.30	0.25	0.22	ACS
Renter %	0.50	0.21	0.53	EU
Average household size	2.81	0.65	2.80	EU
Elderly %	0.34	0.23	0.32	ACS
Young child %	0.22	0.14	0.20	ACS
Detached %	0.32	0.30	0.22	ACS
Average building age	74.32	18.74	77.69	EU

a. Energy Usage 2010 (City of Chicago)
b. 2010 Decennial Census
c. Smart Location Database
d. National Land Cover Database 2011
e. USGS AVHRR Remote Sensing Phenology Metrics
f. American Community Survey 5-year estimate 2009-2013

Regarding the analytical method, this study uses a spatial error model that harnesses spatially dependent observations. When the observations are spatially adjacent to each other, a spatial autocorrelation issue is likely to arise for the following reasons: (1) data collection units (i.e., block group boundaries in this study) may not accurately represent the nature of the underlying mechanisms behind the observed data patterns; (2) during the data collection process, some determinants that are associated with spatial units, such as microclimates, are unobserved, and these missing data generate a spatial dependency; and (3) there may be interactions between spatial units, such as possible spillovers or diffusion dynamics. In the data, there is a strong spatial autocorrelation among the average energy consumption of neighboring block groups. Thus, it is highly possible that the results of the OLS model lead to biased estimates. In this sense, model construction based on the presumption of spatial dependency better reflects the real world. This study uses a spatial error model that can be expressed as follows:

$$Y = X\beta + u + \lambda W\varepsilon + \xi$$
$$\xi \sim N(0, \sigma),$$

where ε is a vector of error terms, spatially weighted by spatial weights matrix W. λ is the so-called spatial error coefficient, and ξ is a vector of uncorrelated error terms. Y refers to the aforementioned energy consumption variables, and X is a set of independent variables, including six urban form variables and the other control variables. β is a set of coefficients for the independent variables.

Results

Effects of urban form on energy use levels. The spatial error model is estimated by a maximum likelihood estimation approach using the R package *spdep* (Bivand et al., 2011). Table 4.3 presents the first group of estimation results, which explain the variation in energy consumption level (monthly average) per household. The results show a significant relationship between urban form and energy consumption, with some notable differences across seasons.

As expected, higher population density is more likely to decrease the average energy consumption per dwelling unit of a block group. To some extent, this negative association can be attributed to a smaller (average) size of housing units in densely populated areas. However, it was expected that a greater population density would reduce energy use per dwelling unit because the latter variable is closely related to denser housing unit types (e.g., apartments) that have fewer exposed walls and windows. It is important to note that the effects of population density are quite stable across seasons because density is influential in both heating and cooling. Unlike population density, road network density is significant only with regard to summer energy consumption, and its positive coefficient indicates that an increase in road network density can lead to higher residential energy consumption in summer. This finding can be partially explained by rising urban heat effects during the summer. More importantly, in addition to heat from paved surfaces, which is controlled for by the variable for the average percentage of impervious area, both air pollution and traffic noise can interfere with opening windows (Steemers, 2003), which might lead to more air conditioner usage in summer.

Table 4.3 Estimated Coefficients for Energy Consumption Amount

	Annual Average	Normal Season	Summer	Winter	Standardized β (Annual Average)
Intercept	7.490 ***	7.060 ***	5.900 ***	8.197 ***	-0.0005
Population density	-0.008 ***	-0.008 ***	-0.007 ***	-0.008 ***	-0.336 ***
Road network density	0.001	0.001	0.002 *	0.002	0.013
Edge contrast	-0.022 ***	-0.024 ***	-0.008 **	-0.025 ***	-0.096 ***
Average building stories	0.026 ***	0.032 ***	0.020 ***	0.023 ***	0.056 ***
Average impervious area	-0.005 ***	-0.006 ***	-0.001	-0.006 ***	-0.101 ***
Vegetation (NDVI)	0.00003	0.00241	-0.00613 ***	0.00012	0.00023
log(Median income)	0.078 ***	0.071 **	0.141 ***	0.068 **	0.062 ***
High education %	-0.294 ***	-0.323 ***	-0.298 ***	-0.283 ***	-0.110 ***
Renter %	-0.605 ***	-0.554 ***	-0.721 ***	-0.588 ***	-0.193 ***
Average household size	0.168 ***	0.153 ***	0.222 ***	0.168 ***	0.163 ***
Young child %	0.095 **	0.089 **	0.140 ***	0.084 **	0.032 **
Elderly %	0.243 ***	0.241 ***	0.068	0.276 ***	0.049 ***
Detached %	0.632 ***	0.630 ***	0.645 ***	0.631 ***	0.280 ***
Average building age	0.004 ***	0.004 ***	0.002 ***	0.005 ***	0.116 ***
Lambda	0.132	0.117	0.106	0.145	0.132
LR test	15.869	12.505	10.356	19.297	15.869
LM for residual (p-value)	0.9089	0.9147	0.8982	0.9032	0.9089

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Table 4.4 Estimated Coefficients for Energy Consumption Ratios

	Summer/Normal	Winter/Normal	Standardized β (Summer/Normal)	Standardized β (Winter/Normal)
Intercept	-0.450 ***	1.339 ***	-0.0033	-0.0008
Population density	0.0005 ***	-0.006 ***	0.068 ***	-0.158 ***
Road network density	0.002 ***	0.001 ***	0.066 ***	0.078 ***
Edge contrast	0.013 ***	-0.002 **	0.210 ***	-0.057 **
Average building stories	-0.009 ***	-0.008 ***	-0.069 ***	-0.114 ***
Average impervious area	0.0046 ***	0.0001	0.323 ***	-0.021
Vegetation (NDVI)	-0.009 ***	-0.002 ***	-0.211 ***	-0.106 ***
log(Median income)	0.072 ***	0.001	0.212 ***	0.003
High education %	0.001	0.028 *	0.001	0.073 *
Renter %	-0.218 ***	-0.044 **	-0.254 ***	-0.097 **
Average household size	0.082 ***	0.019 ***	0.289 ***	0.129 ***
Young child %	0.056 ***	-0.003	0.069 ***	-0.007
Elderly %	-0.147 ***	0.045 **	-0.109 ***	0.063 **
Detached %	0.072 ***	0.020	0.117 ***	0.062
Average building age	-0.002 ***	0.001 ***	-0.185 ***	0.217 ***
log(Annual average kBTU)	-0.088 ***	-0.028 ***	-0.322 ***	-0.194 ***
Lambda	0.254	0.180	0.254	0.180
LR test	66.594	33.102	66.594	33.102
LM for residual (p-value)	0.6442	0.7513	0.642	0.7513

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Edge contrast is negatively associated with energy consumption in all seasons. This finding contradicts the results reported by Wilson, but it is not surprising given the contextual differences between Chicago and Wilson's (2013) study areas. Unlike the inland counties of Illinois analyzed by Wilson (2013), this study focuses on Chicago, which is adjacent to Lake Michigan, a large body of water. Because water has a higher 'specific heat capacity' (the heat required to increase the temperature of a unit mass) than soil, areas in close proximity to the lake obtain heating benefits in winter and cooling benefits in summer; this phenomenon is known as the 'coastal climate.' Therefore, areas with high edge contrasts have lower energy consumption.

The average number of building stories in a block group is positively associated with residential energy consumption across seasons; high-rise buildings probably use additional energy for public facilities, such as elevators and lighting in hallways. In contrast, the average percentage of impervious areas is negatively related to residential energy usage in winter and normal seasons but has no significance in summer. This result suggests that paved surfaces are more likely to contribute to a higher temperature through heat effects, known as the urban heat island effect, and that these effects are influential in reducing heat energy consumption in winter and normal seasons. However, this heating effect does not decrease the demand for cooling energy in summer; indeed, it may increase demand in a statistically insignificant way.

The vegetation index is significant and negatively related to energy usage only in summer, indicating that more plants are likely to reduce energy use in summer. This finding is in line with previous studies (e.g., Ko and Radke, 2014) demonstrating that plants that provide more shading and heat energy emissions via transpiration have a significant cooling effect in urban areas. However, these effects are statistically insignificant in non-summer seasons, unlike the corresponding effects of impervious areas, which are significant only in winter.

Among socio-economic variables, the median household income of a block group is positively related to energy consumption amounts across seasons. Based on utility maximization theory, positive coefficients can be explained by the fact that higher disposable incomes shift up the budget line and therefore increase overall consumption (unless a good no longer provides additional benefits), including consumption of energy. In addition, it is notable that the impact of income is clearly higher (0.145) in summer than in other seasons (0.072 ~ 0.081). We suspect that this difference is attributable to unobserved factors, such as the relationship between income and cooling appliances such as air conditioners. Specifically, inspecting the top and bottom 10% of the sample, the summer energy consumption of the high-income group consists of 59% electricity and 41% gas, whereas the corresponding consumption of the low-income group consists of 48% electricity and 52% gas. There is no significant difference in the abovementioned compositions in winter; however, the high-income group's energy consumption consists of 9% electricity and 91% gas, whereas the corresponding consumption of the low-income group consists of 8% electricity and 92% gas. This result implies that electricity consumption for cooling appliances is the key driver of the increase in summer energy consumption and that poor residents are unable to use more cooling energy because of relatively high electricity prices.[10]

[10] According to Average Energy Prices information from the Bureau of Labor Statistics, the per-BTU energy price of electricity was 4.8 times more expensive than the unit BTU price of utility gas in the Chicago area in 2010 (i.e., \$0.043 vs. \$0.009).

The percentage of residents with high education shows negative coefficients, suggesting that people with a higher level of educational attainment tend to use less energy. As previously hypothesized, this finding is presumably attributable to the fact that people who are exposed to environmental education tend to adopt pro-environmental attitudes (Clery and Rhead, 2013). The percentage of renters also shows negative coefficients, indicating that renters are likely to consume less energy than owners. This may be attributable to the fact that renters are less likely than homeowners to purchase and install additional appliances either because some landlords do not allow such installations or because renters plan to move.

Nevertheless, and as expected, the coefficients for the average number of people in the household are consistently significant and positive, meaning that more household members living in a housing unit leads to more energy consumption. Furthermore, the percentages of both young children and elderly are significantly and positively associated with energy consumption, except for energy use by the elderly in summer. This finding appears to suggest that physically vulnerable age groups require more residential energy to maintain comfortable indoor conditions.

Housing characteristics, housing type and average building age yield the expected results. The percentage of detached single-family housing has consistently positive impacts across seasons, suggesting that this type of dwelling requires more energy because it has more exposed surfaces, larger floor areas, and higher ceilings. Old buildings generally use more energy, perhaps because of poor thermal efficiency. However, it is notable that the coefficients of building age show a clear difference between summer (0.002) and winter (0.005), which may imply that residents of old buildings are more sensitive to Chicago's severely cold winter weather than to the summer heat.

In addition to the absolute magnitudes of coefficients, each variable's portion of the total impact on energy consumption can provide information about the degree to which urban form factors affect energy consumption. The last column presents estimation results using standardized (β) coefficients, which represent the relative importance of each variable. It is notable that population density is the most influential urban form variable in its effect on energy consumption and that housing characteristics (that is, the percentage of detached single-family units) and average building age are also of considerable importance. Among household characteristics, both tenure status (i.e., the percentage of renter-occupied dwelling units) and the average number of household members are more influential than median income.

In summary, the results show that urban form variables, along with housing and household characteristics, play an important role in the determination of energy consumption. The results also show not only that each urban form factor has a distinct direction and magnitude but also that many urban form variables have notable seasonal variations that indicate the existence of complex relationships between urban form and energy use.

Effects of urban form on energy use ratios between seasons. Table 4.4 presents the results using ratios of energy consumption between seasons as dependent variables (i.e., summer-to-normal or winter-to-normal seasonal ratios). As mentioned earlier, these ratio variables were expected to reveal the different impacts of urban form on heat/cooling energy use and thus provide a better understanding of the complex seasonal variation in the association between urban form and residential energy consumption. Although the use of ratios somewhat normalizes the different levels of energy use across block groups, our analysis of these variables also includes the annual average energy consumption level for each block group to control for scale effects, assuming that the changing ratios of seasonal energy might be influenced by the block groups' energy use levels (e.g., areas with lower energy consumption may have a lower degree of seasonal variation).

Overall, the results suggest that associations between urban form and residential energy use vary considerably across seasons. Whereas population density consistently showed a negative association with the level of energy consumption in the previous model's estimation outcomes, it increases the ratio of summer-to-normal energy use. This finding indicates that when holding other variables fixed, denser areas use more energy in summer than do average block groups. Conversely, higher population density seems to decrease energy use in winter compared to use in other seasons, suggesting that there is a trade-off; that is, high density decreases heating energy use in winter but tends to increase the demand for cooling energy in summer.

Similar to population density, edge contrast increases relative energy use in summer and decreases it in winter. More specifically, a one-standard-deviation increase (2.86 unit) in edge contrast leads to a 3.7% increase in the ratio between summer and normal energy use, whereas the same increase in edge contrast induces a 0.6% decrease in energy use in winter. This finding is largely consistent with previous findings on energy use, namely that the lake may provide some heating support in winter but may also increase sensible temperature by creating additional humidity in summer and thus increase the demand for cooling energy. The average percentage of impervious area also shows the same seasonal effects as population density and edge contrast, but the coefficient in the winter-to-normal model is not significant. In other words, paved surfaces generate adverse effects in summer through the urban heat island effect but do not significantly reduce energy consumption in winter compared to other seasons.

Road network density shows positive effects on energy use in both the summer-to-normal and winter-to-normal models, indicating that denser road networks might induce a meaningful increase in energy consumption in summer and winter compared to other seasons. This finding may imply that a denser road network increases the energy demands of nearby residents, presumably because noise and air pollution from roads interrupt natural ventilation in summer and roads between buildings create stronger wind path in winter. The difference between the two coefficients is not considerably large.

Two urban form variables reduce both summer-to-normal and winter-to-normal ratios: the average number of building stories (-0.008 ~ -0.009) and the vegetation variables (-0.008 ~ -0.002). This finding indicates that these variables have higher mitigating effects in hot and cold weather than in moderate temperatures. The negative impacts of average number of building stories on these ratios can be explained by the better insulation efficiencies of multifamily housing units, as suggested by Ko (2013). More specifically, multifamily housing units that have smaller areas exposed to the outdoor climate can save additional heating and cooling energy during winter and summer, respectively. However, an increase in the average number of building stories is positively associated with the amount of energy used per dwelling unit; therefore, the net energy conservation benefits are indeterminate.

Similarly, the vegetation index shows negative impacts on both summer-to-normal and winter-to-normal ratios. However, in contrast to the average number of building stories, the vegetation index has no amplifying effects on the amount of energy used, as shown in Table 4.3. Trees and green surfaces can reduce both energy consumption amounts and their seasonal variation, which is quite beneficial for energy conservation. Additionally, it is interesting that the magnitude of the coefficient is significantly higher in the summer-to-normal model, indicating stronger benefits in summer than in winter.

Some socio-economic variables also show notable seasonal patterns. Median household income, for example, has a positive association with the summer-to-normal ratio but exhibits an opposite coefficient in the winter-to-normal ratio model. This finding indicates that affluent areas tend to increase their summer energy consumption above the average but use relatively less energy during the winter. Although higher educational attainment decreased energy consumption in the previous model, it does not show any significant impact on the ratios. The percentage of renter-occupied housing has negative coefficients in all models, suggesting that with respect to energy consumption, homeowners have a higher degree of seasonal variation than do renters.

Regarding demographic factors, average household size shows positive coefficients, suggesting that a larger number of people living in a dwelling unit can lead to higher demand for heating and cooling energy. Additionally, the percentage of children under 6 is positively associated with the summer-to-normal energy use ratio but has no significant effects on the winter-to-normal ratio, which may imply that households with children use more cooling energy than does the average household. In contrast, block groups with more elderly people tend to consume less cooling energy in summer and more energy in winter.

An increase in the percentage of detached single-family units is positively associated with higher-than-average energy consumption in summer, but no statistically significant effects are detected in the winter-to-normal model. Considering the previous results in Table 4.3, single-family detached homes increase overall energy use but increase energy demand considerably in summer. In contrast, building age is positively associated with the summer-to-normal energy use ratio but negatively related to the winter-to-normal ratio. Regarding the annual average per-household energy consumption variable, areas involving a greater amount of energy consumption tend to have a smaller summer-to-normal energy consumption ratio, suggesting that the increase in the rate of energy use between normal to summer months is likely to be smaller in these energy-intensive areas.

Columns #3 and #4 in Table 4.4 present the beta coefficients of each ratio model. Although population density, which employs the amount of energy use as dependent variable, is the most influential (-0.336) urban form variable in Table 4.3, the beta coefficient of population density is relatively small in the ratio models (0.068 and -0.158, respectively). In contrast, the percentage of impervious area (0.321) and edge contrast (0.205) appear to contribute significantly to the increase in the summer-to-normal ratio but show moderate effects on average energy consumption and in the winter-to-normal models. The vegetation index is higher (-0.206 ~ -0.111) in the ratio models but is not significant in the energy use amount model, indicating that plants are more effective at reducing energy-use fluctuation across seasons. It is also notable that more than in other models, household characteristics tend to have greater beta coefficients in the summer-to-normal ratio model, which implies that human factors play a more important role in relative energy consumption in summer than in normal seasons. This finding may be further investigated in future research.

Sensitivity Analysis. In an analysis involving spatial units, varying spatial scopes often generate inconsistent outcomes because each spatial boundary used for data aggregation can yield different patterns with the same raw data. This problem is commonly referred to as the 'modifiable areal unit problem' (Fotheringham and Wong, 1991), and it also affects this study. In particular, by their nature, urban forms are spatial variables; therefore, different spatial scopes can have distinct implications. In this sense, analyzing the data with changed spatial levels and examining differences in the results helps us better understand the interactions between urban form and energy consumption.

Although there are two options, scaling up (census tract) and scaling down (block), the latter option was removed because the ACS does not provide some datasets at the block level; therefore, applying block group data to sub-areas (block) might result in inaccurate outcomes. Therefore, this study conducts census tract-level analysis using only 781 observations.

Table 4.5 reports the results using data aggregated by census tracts, and the results are comparable to those in Table 4.3. Population density, average number of building stories, average impervious area, and vegetation variables show values consistent with the block group-level results. However, road network density becomes significant for annual average and winter energy consumption, and their overall magnitude increases, which may imply that influences from road networks are more effective on a broader scale (for example, inter-connected neighborhoods relative to individual blocks). In contrast, the magnitudes of edge contrast decrease in census tracts, but the negative effect becomes stronger and significant in summer. Thus, contrasting land uses between census tracts generally have weaker mitigating effects on energy consumption in cooler seasons, although the edge contrast at the broader level has meaningful cooling effects compared to the block group level. In summary, these variances may imply that urban forms can be viewed differently at different spatial scales; some urban forms may reveal stronger influences at larger scales, whereas others require narrower spatial scales.

Regarding the control variables, the directions and significances of the coefficients are similar to the results in Table 4.3, although there are some exceptional cases. For example, high educational levels and a high percentage of young children under 6 lose their significance, which may be attributable to the fact that changing the spatial scope leads to considerably different correlations among variables. Indeed, the correlation between the percentage of young children and income increases from 0.18 to 0.39, and the correlation between high education and income increases from 0.63 to 0.72. Although some changes do occur, the general pattern of the relationship between urban form and energy consumption remains similar, strengthening the findings of this study.

We also derive estimations using inter-season ratios. Table 4.6 reports the results, which can be paired with those in Table 4.4. Overall, the effects of urban forms at the census tract level appear to be similar to the previous results based on block groups, but the magnitudes and significances of the results differ. For example, the magnitudes of population density, average impervious area, and vegetation index are smaller for the tract-based estimations, whereas the impacts of road density, magnitudes of edge contrast, and average number of building stories increase in both models in summer. In addition, the control variables change in statistical significance and magnitude but do not give rise to conflicting outcomes by, for example, reversing the direction of the results. Consequently, although a spatial scope issue may have compromised the results, our findings nevertheless prove reliable.

Table 4.5 Estimated Coefficients for Energy Consumption Amount (Based on Census Tract)

	Annual Average	Normal	Summer	Winter
Intercept	6.411 ***	6.110 ***	4.956 ***	7.021 ***
Population density	-0.0076 ***	-0.0072 ***	-0.0061 ***	-0.0078 ***
Road network density	0.004 *	0.003	0.005 **	0.004 *
Edge contrast	-0.017 ***	-0.018 ***	-0.005	-0.018 ***
Average building stories	0.0276 **	0.031 **	0.0001	0.0295 **
Average impervious area	-0.0060 ***	-0.0062 ***	-0.0013	-0.0065 ***
Vegetation (NDVI)	-0.0025	0.0003	-0.0089 ***	-0.0023
log(Median income)	0.154 ***	0.146 ***	0.224 ***	0.148 ***
High education %	-0.141	-0.164	-0.223 *	-0.119
Renter %	-0.265 **	-0.262 *	-0.458 ***	-0.242 *
Average household size	0.216 ***	0.190 ***	0.237 ***	0.228 ***
Young child %	-0.115	-0.118	-0.069	-0.119
Elderly %	0.442 ***	0.440 ***	0.148	0.482 ***
Detached %	0.766 ***	0.788 ***	0.746 ***	0.762 ***
Average building age	0.004 ***	0.003 ***	0.001 *	0.004 ***

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Table 4.6 Estimated Coefficients for Energy Consumption Ratio (Based on Census Tract)

	Summer/Normal	Winter/Normal
Intercept	-0.284	0.927 ***
Population density	0.0009 ***	-0.0008 ***
Road network density	0.001 *	0.001 *
Edge contrast	0.0054 ***	0.0004
Average building stories	-0.034 ***	-0.002
Average impervious area	0.0025 ***	-0.0004
Vegetation (NDVI)	-0.004 ***	-0.002
log(Median income)	0.040 ***	0.032 ***
High education %	-0.085 **	0.024
Renter %	-0.200 ***	-0.004
Average household size	0.025 *	0.039 ***
Young child %	0.017	-0.021
Elderly %	-0.180 ***	0.066 *
Detached %	0.008	0.002
Average building age	-0.001 ***	0.002 ***
log(Annual average kBTU)	-0.054 ***	-0.039 ***

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Conclusion

Building on the growing literature on the nexus between urban forms and energy consumption, this study examines how urban forms influence residential energy uses and how the contributions of urban forms to energy consumption vary by season. Using detailed data from the city of Chicago, this study shows that urban forms can have varying effects in different seasonal settings. For example, population density reduces relative energy consumption in winter compared to non-extreme seasons. However, population density has the greatest effects on energy consumption in summer. Although the presence of more plants consistently decreases energy use across the year, the magnitude of this effect is significantly greater in summer. Furthermore, the range of standardized impacts varies by season. In other words, an urban form with a dominant influence in summer may be less influential in winter. In an impervious area, this urban form variable has the greatest standardized impact in summer and a negligibly small effect in winter.

Interestingly, socio-economic factors also show seasonal variations. Median income and household size exhibit stronger and more increasing effects in summer than in winter, whereas educational attainment is more influential in decreasing energy demands in winter. Demographic factors affect the seasonal variation of energy consumption. Specifically, in households with more young children (under 6 years), cooling demands in summer grow, whereas the presence of an elderly population (over 65) is positively associated with heating demands in winter.

Overall, these findings imply a complex nexus between urban form and residential energy consumption. However, it should be emphasized that the complicated seasonal pattern of energy use determinants found in this study is also bound to a certain location: the city of Chicago. As mentioned in the results section, one study that reveals this location-specific aspect is that by Wilson (2013), who yields contrasting results with edge contrasts in the same region (Illinois). If other study areas that have distinct environmental settings (e.g., Los Angeles) are analyzed, different outcomes may emerge, and each urban form obviously has different implications for energy consumption. Future studies can also explore how these inter-area differences are structurally associated with various explanatory factors.

For policy-makers, this study argues that there is no best urban form that reduces energy consumption universally. Therefore, before making energy policies that use urban form as an instrument, policy-makers need to thoroughly investigate the characteristics of an area and the particular impacts of urban forms, while also considering other surrounding factors. Additionally, given the rapidly changing climate (so-called global warming), it should be highlighted that the effects of urban form on energy use also change over time. In this sense, a better urban form (while not the best) is a more responsive one that can keep pace with changes in the surrounding environment. For this reason, policy-makers can aim to develop more diverse urban forms in order to reduce potential risks from unexpected changes (a similar logic to a diversified investment portfolio) and can attempt to make smaller-scale adjustments that have milder impacts on the complicated nexus between urban form and energy consumption.

It is expected that in future studies, more sophisticated data measures and richer data sources will support efforts to understand the complexity of urban form and energy consumption more deeply. While this study is limited by its use of aggregated-level analysis, which is related to data availability, future research can incorporate additional measures such as LiDAR (Light Detection and Ranging)-based building volume, tree crown and shade area, building shape and direction, exterior materials, number of windows, and micro-climates. Additionally, given the importance of peak-time energy demand, an investigation of how urban forms affect daily fluctuations in energy demand would provide meaningful insights for policy-makers.

CHAPTER 5

Summary and Discussion

The present dissertation attempts to shed light on the complexity of residential energy consumption, which is associated with various determinants that stem from multiple disciplines, including economics, psychology, physics, and planning. To accomplish its goal, this study employs detailed data concerning households, housing units, and their surrounding environments and engages in three interrelated studies, each of which has a distinct focus corresponding with the research design. The findings of these empirical analyses reveal the dynamics of energy consumption determinants that have different and sometimes even contrasting influences in both the social and environmental contexts, and hence, they indicate that the mechanisms determining residential energy consumption are very complicated.

The first study investigates how the micro-level dynamics of household influence energy consumption in dwelling units over the course of the residence period, assuming that the household's relocation functions as a "trigger" that brings attention to energy efficiency and that longer exposure to the same living environment makes households prefer the "status quo" and its settled energy consumption patterns. For the analysis, this study builds a panel dataset using the AHS from 2001 to 2013. It is found that households who have recently relocated tend to use smaller amounts of energy, and as the period of residence increases, their level of energy consumption rises. In addition, recent movers are more likely to be influenced by external factors, such as energy price and heating/cooling degree days; meanwhile, households who have lived in the same housing units for longer periods are more influenced by internal factors, such as the number of household members and income. In analysis models using interaction variables, the results indicate that a higher household income, along with the residence period, accelerates the increase in energy consumption, and a severe climate tends to reduce the speed of that increase. Additionally, various combinations of tenure and housing unit types, along with the period of residence, are found to result in different changes in energy consumption patterns. In a quasi-experimental study that compares a set of mover-stayer pairs, similar results are found. These findings support the existence of temporal dynamics pertinent to the household's relocation and period of residence.

The second study focuses on the inter-agent dynamics that exist in decision-making processes regarding the adoption of solar energy systems. This study pays explicit attention to the problem of split of incentives and/or the problem of split decision-making, which are shaped by combinations of homeownership, utility payment status, and housing type, and it examines the impacts of these problems on the probability of solar energy system adoption in the U.S. Using a logistic regression model with two national datasets (i.e., RECS and ACS), the empirical results reveal that these problems impede the adoption of solar energy systems to a statistically significant extent. Interestingly, renter-occupied multifamily households who do not pay utility fees have a similar or higher probability of solar energy system adoption than do owner-occupied single-family households who do pay utility fees. This finding is attributed to the fact that renter-occupied multifamily buildings are generally owned by a single entity, such as a rental company, and therefore, the single owner has enough motivation to improve the building's energy efficiency and also has a greater ability to manage the installation processes.

The third study, which is more planning-oriented, attempts to investigate the relationship between various urban forms and residential energy consumption with explicit consideration of seasonality using geographically continuous data from the city of Chicago. For the analysis, six urban form indicators are measured at the block group level, including density, edge contrast, number of building stories, impervious area, and vegetation. The estimation results obtained using a spatial error model demonstrate that these urban forms are found to have statistically significant relationships with energy usage, and furthermore, they reveal different and sometimes contrasting effects by season. For example, an increase in population density, which is generally believed to be a good way to reduce energy consumption, has negative association with energy consumption amounts across the seasons. However, increased population density is found to intensify relative energy use in summer due to poorer ventilation and higher demands for cooling in multifamily buildings. These empirical findings imply a dynamic relationship between residential energy use and the surrounding environment, and they therefore suggest that energy-related planning policies should be based on a thorough understanding of the target area, especially the different effects generated by the interaction between urban forms and climate.

In sum, this dissertation explores the dynamics of residential energy consumption at multiple dimensions and provides evidence revealing the complex mechanisms that determine residents' energy-related choices. This complexity is found to influence a household's energy use patterns over time, decision-making processes among different agents, and the effects of the built environment according to the season. One implication of these findings is that there is no panacea to address energy issues; that is, a solution that is effective in one place may not work in other places. Rather, the dynamic aspects of residential energy consumption suggest that policy-makers and planners should prudently approach each policy target by thoroughly investigating various socio-economic, demographic, behavioral, and physical factors and their dynamic relationships in order to establish sophisticated energy policies that better fit their social and environmental contexts.

This dynamic nature of residential energy consumption further suggests policies that are more reversible and flexible, or so-called adaptive policies (Walker et al., 2001; Allen et al., 2011; Rist et al., 2013; Feldman, 2017). This approach attempts to alleviate the unexpected side effects triggered by one-shot policies that make large changes at once. Instead, the adaptive approach suggests imposing policies that have small-scale, reversible, and incremental impacts, and after those policies are implemented, there must be continuous monitoring and assessment of the effects. Then, policies can be adjusted and/or developed based on that feedback. This approach is expected to better serve society with regard to developing more efficient policies targeting the complicated mechanism of residential energy consumption; such an approach may also help in adjusting a policy when the efficiency point shifts with contextual changes. Adaptive policy management also emphasizes embracing public concerns and inducing local participation in such a way that energy-related policies can utilize multiple instruments, including behavioral, economic, and contextual tools.

Additionally, both building sophisticated policy based on the detailed characteristics of targets and adaptive policy management based on monitoring policy outcomes naturally demand firmer foundations to stand on; in the field of residential energy consumption, this foundation is data collection. In particular, micro-level data gathered with higher frequency, in larger volume, and at various layers – so-called big data – can assist energy policies by providing a basis for conducting analysis and capturing feedback. Recent technological innovations, such as the Internet of Things (IoT) and the Smart City, also support the generation of big data through the utilization of micro sensors (Jha et al., 2015; Reis et al., 2015). Some pioneering companies are already moving in this direction: for instance, Bosch has launched a climate and air pollution monitoring system packed in a small box, called Climo, and SK (a Korean company) has started a project called Weatherplanet, which integrates weather sensors with the company's cellular network sites. These examples emphasize the importance of public-private partnerships in taking advantage of the velocity and efficiency of private sectors while also serving public interests.

As energy-related data becomes bigger, faster and more varied, it is recommended that policy-makers utilize more advanced approaches that handle big data more effectively, such as artificial neural networks and genetic models, which can efficiently manage larger datasets with fewer statistical concerns (e.g., multicollinearity) (Garg and Tai, 2012). It is notable that numerous studies on building energy consumption have used these machine learning approaches, which yield higher prediction power than do statistical prediction models (Kalogirou, 2000; Aydinalp et al., 2004; Ben-Nakhi and Mahmoud, 2004; González and Zamarreño, 2005; Yang et al., 2005; Karatasou et al., 2006; Neto and Fiorelli, 2008; Wong et al., 2010; Li et al., 2011; Swan et al., 2012; Buratti et al., 2014; Biswas et al., 2016). Given the growing availability of larger and micro-level data, these methodologies are expected to provide useful policy tools; for instance, simulating energy consumption patterns based on different scenarios of population growth, economic development, or demographic changes.

Finally, it is worth noting that technical changes often result in socio-economic changes. In the residential energy field, the tacit assumption is that residents are passive consumers. However, increased attention is being paid to smart grids and distributed (or decentralized) generation technologies, such as solar energy production at the residential building level, and these technologies can transform residents from consumers to prosumers (Toffler, 1981) by enabling them to generate electricity for themselves and sell the extra energy to other households or companies on the grid (Adil and Ko, 2016; Yazdanie et al. 2016). While practically, this change provides great opportunities to save energy costs and reduce greenhouse gases (Akorede et al., 2010; Willman and Krarti, 2013; Poudineh and Jamasb, 2014), from a broader perspective, this new paradigm can trigger structural changes in energy-use (as well as energy-production) patterns, and thus our existing knowledge probably needs to be revisited. There are many unexplored, or even unidentified, areas in the field of energy, and venturing into these new territories is not easy. Although I do not believe that planners can accomplish this task alone, I do believe that long-term interdisciplinary efforts can achieve our higher goals of understanding the nature of energy consumption and can empower us to make that consumption more sustainable.

REFERENCES

Adil, A. M., & Ko, Y. (2016). Socio-technical evolution of Decentralized Energy Systems: A critical review and implications for urban planning and policy. *Renewable and Sustainable Energy Reviews*, *57*, 1025–1037.

Aigner, D. J., Sorooshian, C., & Kerwin, P. (1984). Conditional demand analysis for estimating residential end-use load profiles. *The Energy Journal*, *5*(3), 81-97.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211.

Akorede, M. F., Hizam, H., & Pouresmaeil, E. (2010). Distributed energy resources and benefits to the environment. *Renewable and Sustainable Energy Reviews*, *14*(2), 724-734.

Alberini, A., Gans, W., & Velez-lopez, D. (2011). Residential consumption of gas and electricity in the U.S.: The role of prices and income. *Energy Economics*, *33*(5), 870–881.

Allen, C. R., Fontaine, J. J., Pope, K. L., & Garmestani, A. S. (2011). Adaptive management for a turbulent future. *Journal of Environmental Management*, *92*(5), 1339-1345.

Altmann, E. (2014). Apartments, Co-ownership and Sustainability: Implementation Barriers for Retrofitting the Built Environment. *Journal of Environmental Policy and Planning*, *16*(4), 437–457.

Ang, B. W., Goh, T. N., & Liu, X. Q. (1992). Residential electricity demand in Singapore. *Energy*, *17*(1), 37-46.

Arisoy, I., & Ozturk, I. (2014). Estimating industrial and residential electricity demand in Turkey: a time varying parameter approach. *Energy*, *66*, 959-964.

Armitage, C. J., & Conner, M. (2001). Efficacy of the theory of planned behaviour: A meta-analytic review. *British Journal of Social Psychology*, 40(4), 471-499.

Aydinalp, M., Ugursal, V. I., & Fung, A. S. (2004). Modeling of the space and domestic hot-water heating energy-consumption in the residential sector using neural networks. *Applied Energy*, *79*(2), 159-178.

Aydinalp, M., Ugursal, V. I., & Fung, A. S. (2004). Modeling of the appliance, lighting, and space- cooling energy consumptions in the residential sector using neural networks. *Applied Energy*, *71*, 87–110.

Baker, P., Blundell, R., & Micklewright, J. (1989). Modelling household energy expenditures using micro-data. *The Economic Journal*, 720-738.

Bauner, C., & Crago, C. L. (2015). Adoption of residential solar power under uncertainty: Implications for renewable energy incentives. *Energy Policy*, *86*, 27-35.

Belaïd, F. (2016). Understanding the spectrum of domestic energy consumption: Empirical evidence from France. *Energy Policy*, *92*, 220-233.

Ben-Nakhi, A. E., & Mahmoud, M. A. (2004). Cooling load prediction for buildings using general regression neural networks. *Energy Conversion and Management*, *45*(13–14), 2127–2141.

Berkhout, P. H., Muskens, J. C., & Velthuijsen, J. W. (2000). Defining the rebound effect. *Energy Policy*, *28*(6), 425-432.

Biswas, M. A. R., Robinson, M. D., & Fumo, N. (2016). Prediction of residential building energy consumption: A neural network approach. *Energy*, *117*, 84–92.

Bivand, R., Anselin, L., Berke, O., Bernat, A., Carvalho, M., Chun, Y., ... & Lewin-Koh, N. (2011). spdep: Spatial dependence: weighting schemes, statistics and models.

Black, J. S., Stern, P. C., & Elworth, J. T. (1985). Personal and contextual influences on household energy adaptations. *Journal of Applied Psychology*, *70*(1), 3.

Brager, G. S., & de Dear, R. J. (1998). Thermal adaptation in the built environment: A literature review. *Energy and Buildings*, *27*(1), 83-96.

Branch, E. R. (1993). Short run income elasticity of demand for residential electricity using consumer expenditure survey data. *The Energy Journal*, 111-121.

Brounen, D., Kok, N., & Quigley, J. M. (2012). Residential energy use and conservation: Economics and demographics. *European Economic Review*, *56*(5), 931-945.

Brownstone, D., & Golob, T. F. (2009). The impact of residential density on vehicle usage and energy consumption. *Journal of Urban Economics*, *65*(1), 91–98.

Buratti, C., Barbanera, M., & Palladino, D. (2014). An original tool for checking energy performance and certification of buildings by means of Artificial Neural Networks. *Applied Energy*, *120*, 125–132.

Calcerano, F., & Martinelli, L. (2016). Numerical optimisation through dynamic simulation of the position of trees around a stand-alone building to reduce cooling energy consumption. *Energy and Buildings*, *112*, 234–243.

Camerer, C. F., Loewenstein, G., & Rabin, M. (Eds.). (2011). *Advances in behavioral economics*. Chapter 1, Princeton University Press

Cervero, R., & Kockelman, K. (1997). Travel demand and the 3Ds: Density, diversity, and design. *Transportation Research Part D: Transport and Environment*, *2*(3), 199–219.

Chen, J., Wang, X., & Steemers, K. (2013). A statistical analysis of a residential energy consumption survey study in Hangzhou, China. *Energy and Buildings*, *66*, 193-202.

Clery, E and Rhead, R. (2013). Education and attitudes towards the environment. *Background Paper Prepared for the Education for All Global Monitoring Report 2013*, *4*.

Cook, J. J., Ardani, K. B., Margolis, R. M., & Fu, R. (2018). *Cost-Reduction Roadmap for Residential Solar Photovoltaics (PV), 2017-2030* (No. NREL/TP-6A20-70748). National Renewable Energy Lab.(NREL), Golden, CO (United States).

Davis, L. W. (2011). Evaluating the slow adoption of energy efficient investments: are renters less likely to have energy efficient appliances? In *The Design and Implementation of US Climate Policy* (pp. 301-316). University of Chicago Press.

De Dear, R. J., Brager, G. S., Reardon, J., & Nicol, F. (1998). Developing an adaptive model of thermal comfort and preference/discussion. *ASHRAE Transactions*, *104*, 145.

De Dear, R., & Brager, G. S. (2001). The adaptive model of thermal comfort and energy conservation in the built environment. *International Journal of Biometeorology*, *45*(2), 100-108.

De Maesschalck, R., Jouan-Rimbaud, D., & Massart, D. L. (2000). The mahalanobis distance. *Chemometrics and Intelligent Laboratory Systems*, *50*(1), 1-18.

De T'Serclaes, P. (2007). Financing energy efficient homes. *IEA Information Paper. Paris, France*.

De Vita, G., Endresen, K., & Hunt, L. C. (2006). An empirical analysis of energy demand in Namibia. *Energy Policy*, *34*(18), 3447-3463.

Delmastro, C., Mutani, G., Pastorelli, M., & Vicentini, G. (2015). Urban morphology and energy consumption in Italian residential buildings Urban morphology and energy consumption in Italian residential buildings. *4th International Conference on Renewable Energy Research and Applications*, *5*(January 2016), 1603–1608.

Dennerlein, R. K. H. (1987). Residential demand for electrical appliances and electricity in the Federal Republic of Germany. *The Energy Journal*, *8*(1), 69-86.

Dieleman, F. M., Clark, W. A., & Deurloo, M. C. (2000). The geography of residential turnover in twenty-seven large US metropolitan housing markets, 1985-95. *Urban Studies*, 37(2), 223-245.

Donatos, G. S., & Mergos, G. J. (1991). Residential demand for electricity: the case of Greece. *Energy Economics*, *13*(1), 41-47.

Douthitt, R. A. (1989). An economic analysis of the demand for residential space heating fuel in Canada. *Energy*, 14(4), 187-197.

Dubin, J. A., & McFadden, D. L. (1984). An econometric analysis of residential electric appliance holdings and consumption. Econometrica: *Journal of the Econometric Society*, 345-362.

EIA (2017). *Annual Energy Overlook*

EIA (2017). *Annual Energy Review*

Elsawaf, N., Abdel-Salam, T., & Pagliari, L. (2012). Evaluation of heat pumps usage and energy savings in residential buildings. *International Journal of Energy and Environment*, *3*(3), 399-408.

Estiri, H. (2015). A structural equation model of energy consumption in the united states: untangling the complexity of per-capita residential energy use. *Energy Research & Social Science*, *6*, 109-120.

Ewing, R., & Rong, F. (2008). The impact of urban form on U.S. residential energy use. *Housing Policy Debate*, *19*(1), 1–30.

Frederick, S., Loewenstein, G., & O'donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of Economic Literature*, *40*(2), 351-401.

Filippini, M., & Pachauri, S. (2004). Elasticities of electricity demand in urban Indian households. *Energy Policy*, *32*(3), 429-436.

Fogg, B. J. (2009). A behavior model for persuasive design. Paper presented at the Proceedings of the 4th international Conference on Persuasive Technology.

Fotheringham, A. S., & Wong, D. W. S. (1991). The Modifiable Areal Unit Problem in Multivariate Statistical Analysis. *Environment and Planning A*, *23*(7), 1025–1044.

Fuller, S., & Bulkeley, H. (2013). Changing countries, changing climates: Achieving thermal comfort through adaptation in everyday activities. *Area*, *45*(1), 63–69.

Fumo, N., & Biswas, M. R. (2015). Regression analysis for prediction of residential energy consumption. *Renewable and Sustainable Energy Reviews*, *47*, 332-343.

Gans, W., Alberini, A., & Longo, A. (2013). Smart meter devices and the effect of feedback on residential electricity consumption: Evidence from a natural experiment in Northern Ireland. *Energy Economics*, *36*, 729-743.

Garbacz, C. (1983). A model of residential demand for electricity using a national household sample. *Energy Economics*, *5*(2), 124-128.

Garcia-Cerrutti, L. M. (2000). Estimating elasticities of residential energy demand from panel county data using dynamic random variables models with heteroskedastic and correlated error terms. *Resource and Energy Economics*, *22*(4), 355-366.

Garg, A., & Tai, K. (2012). Comparison of regression analysis, artificial neural network and genetic programming in handling the multicollinearity problem. *In Modelling, Identification & Control (ICMIC), 2012 Proceedings of International Conference on* (pp. 353-358). IEEE.

Gillingham, K., Harding, M., & Rapson, D. (2012). Split incentives in residential energy consumption. *Energy Journal*, 33(2), 37-62.

Gintis, H. (2000). Beyond homo economicus: Evidence from experimental economics. *Ecological Economics*, *35*(3), 311-322.

González, P. A., & Zamarreño, J. M. (2005). Prediction of hourly energy consumption in buildings based on a feedback artificial neural network. *Energy and Buildings*, *37*(6), 595–601.

Greening, L. A., Greene, D. L., & Difiglio, C. (2000). Energy efficiency and consumption—the rebound effect—a survey. *Energy Policy*, *28*(6), 389-401.

Grossman, S. J., & Hart, O. D. (1983). An analysis of the principal-agent problem. *Econometrica: Journal of the Econometric Society*, 7-45.

Guagnano, G. A., Stern, P. C., & Dietz, T. (1995). Influences on attitude-behavior relationships a natural experiment with curbside recycling. *Environment and Behavior*, *27*(5), 699-718.

Gujarati, D. N. (2003). *Basic econometrics*. New York: McGraw-Hill Education.

Halicioglu, F. (2007). Residential electricity demand dynamics in Turkey. *Energy Economics*, *29*(2), 199-210.

Hartman, R. S., Doane, M. J., & Woo, C. K. (1991). Consumer rationality and the status quo. *The Quarterly Journal of Economics*, *106*(1), 141-162.

Hemsath, T. L. (2016). Housing orientation's effect on energy use in suburban developments. *Energy and Buildings*, *122*, 98–106.

Holtedahl, P., & Joutz, F. L. (2004). Residential electricity demand in Taiwan. *Energy Economics*, *26*(2), 201-224.

Houde, S., & Todd, A. (2011). List of Behavioral Economics Principles That Can Inform Energy Policy. Lawrence Berkeley National Lab and Precourt Energy Efficiency Center at Stanford University.

Houthakker, H. S. (1951). Some calculations on electricity consumption in Great Britain. *Journal of the Royal Statistical Society. Series A (General)*, *114*(3), 359-371.

Huang, Y. J., Akbari, H., Taha, H., & Rosenfeld, A. H. (1987). The potential of vegetation in reducing summer cooling loads in residential buildings. *Journal of Climate and Applied Meteorology*, 26(9), 1103-1116.

IEA (2017). *Key World Energy Statistics*

Jaffe, A. B., & Stavins, R. N. (1994). The energy-efficiency gap What does it mean? *Energy Policy*, 22(10), 804-810.

Jha, M., Marpu, P. R., Chau, C. K., & Armstrong, P. (2015, October). Design of sensor network for urban micro-climate monitoring. In *Smart Cities Conference (ISC2), 2015 IEEE First International* (pp. 1-4). IEEE.

Kalogirou, S. (2000). Artificial neural networks for the prediction of the energy consumption of a passive solar building. *Energy*, *25*(5), 479–491.

Karatasou, S., Santamouris, M., & Geros, V. (2006). Modeling and predicting building's energy use with artificial neural networks: Methods and results. *Energy and Buildings*, *38*(8), 949–958.

Karlin, B. (2014). Residential energy feedback: Research, technology, and potential for the informed home (Doctoral dissertation, University of California, Irvine).

Kaza, N. (2010). Understanding the spectrum of residential energy consumption: A quantile regression approach. *Energy Policy*, *38*(11), 6574–6585.

Kelly, S. (2011). Do homes that are more energy efficient consume less energy?: A structural equation model of the English residential sector. *Energy*, *36*(9), 5610-5620.

Kialashaki, A., & Reisel, J. R. (2013). Modeling of the energy demand of the residential sector in the United States using regression models and artificial neural networks. *Applied Energy*, *108*, 271-280.

Kim, J. H. (2014). Residential and job mobility: Interregional variation and their interplay in US metropolitan areas. *Urban Studies*, 51(13), 2863-2879.

Kim, J. H., Cho, J., & Keane, T. D. (2015) Political fragmentation and land use changes in the Interior Plains. *Population and Environment*, *37*(1), 63-82.

Kirby, K. N., & Herrnstein, R. J. (1995). Preference reversals due to myopic discounting of delayed reward. *Psychological Science*, *6*(2), 83-89.

Ko, Y. (2013). Urban form and residential energy use: A review of design principles and research findings. *Journal of Planning Literature*, *28*(4), 327-351.

Ko, Y., & Radke, J. D. (2014). The effect of urban form and residential cooling energy use in Sacramento, California. *Environ. Plann. B Plann. Des.*, *41*(4), 573–593.

Komatsu, S., Kaneko, S., Shrestha, R. M., & Ghosh, P. P. (2011). Nonincome factors behind the purchase decisions of solar home systems in rural Bangladesh. *Energy for Sustainable Development*, *15*(3), 284–292.

Krishnamurthy, C. K., and Kriström, B. (2015). How Large is the Owner-Renter Divide? Evidence from an OECD cross-section. *Energy Journal*, *36*(4).

Kwan, C. L. (2012). Influence of local environmental, social, economic and political variables on the spatial distribution of residential solar PV arrays across the United States. *Energy Policy*, *47*, 332–344.

Laverne, Robert J and Lewis, G. M. (1996). The effect of vegetation on residential energy use in Ann Arbor, Michigan. *Journal of Arboriculture*, *22*, 234--243.

Levinson, A., & Niemann, S. (2004). Energy use by apartment tenants when landlords pay for utilities. *Resource and Energy Economics*, 26(1), 51-75.

Lewis, P. G. (2015). Moral intuitions and smart growth: why do liberals and conservatives view compact development so differently? *Journal of Urban Affairs*, *37*(2), 87-108.

Li, K., Su, H., & Chu, J. (2011). Forecasting building energy consumption using neural networks and hybrid neuro-fuzzy system: A comparative study. *Energy and Buildings*, *43*(10), 2893–2899.

Loewenstein, G., & Prelec, D. (1992). Anomalies in intertemporal choice: Evidence and an interpretation. *The Quarterly Journal of Economics*, *107*(2), 573-597.

Lutzenhiser, L. (1992). A cultural model of household energy consumption. *Energy*, *17*(1), 47-60.

Maruejols, L., & Young, D. (2011). Split incentives and energy efficiency in Canadian multi-family dwellings. *Energy Policy*, *39*(6), 3655–3668.

McCright, A. M., & Dunlap, R. E. (2011). The politicization of climate change and polarization in the American public's views of global warming, 2001–2010. *The Sociological Quarterly*, 52(2), 155-194.

McPherson, E. G., & Simpson, J. R. (2003). Potential energy savings in buildings by an urban tree planting programme in California. *Urban Forestry & Urban Greening*, *2*(2), 73–86.

Min, J., Hausfather, Z., & Lin, Q. F. (2010). A high-resolution statistical model of residential energy end use characteristics for the United States. *Journal of Industrial Ecology*, 14(5), 791-807.

Morss, M. F., & Small, J. L. (1989). Deriving electricity demand elasticities from a simulation model. *The Energy Journal*, 51-76.

Mufson, S. and Mooney, C. (2018, February 12). Trump seeks clean energy cuts, $2 billion nuclear spending boost for Energy Dept. Retrieved from https://www.washingtonpost.com

Murtishaw, S., & Sathaye, J. (2006). Quantifying the effect of the principal-agent problem on US residential energy use. *Lawrence Berkeley National Laboratory*.

Nair, G., Gustavsson, L., & Mahapatra, K. (2010). Factors influencing energy efficiency investments in existing Swedish residential buildings. *Energy Policy*, *38*(6), 2956-2963.

Narayan, P. K., & Smyth, R. (2005). The residential demand for electricity in Australia: an application of the bounds testing approach to cointegration. *Energy Policy*, *33*(4), 467-474.

Narayan, P. K., Smyth, R., & Prasad, A. (2007). Electricity consumption in G7 countries: A panel cointegration analysis of residential demand elasticities. *Energy Policy*, *35*(9), 4485-4494.

Nesbakken, R. (1999). Price sensitivity of residential energy consumption in Norway. *Energy Economics*, 21(6), 493-515.

Neto, A. H., & Fiorelli, F. A. S. (2008). Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption. *Energy and Buildings*, *40*(12), 2169–2176.

Newman, P. W. G., & Kenworthy, J. R. (1989). Gasoline consumption and cities: A comparison of U.S. cities with a global survey. *Journal of the American Planning Association*, *55*(1), 24–37.

Nicol, J. F., & Humphreys, M. A. (2002). Adaptive thermal comfort and sustainable thermal standards for buildings. *Energy and Buildings*, *34*(6), 563-572.

Owen, A. D. (2006). Renewable energy: Externality costs as market barriers. *Energy Policy*, *34*(5), 632–642.

Pachauri, S. (2004). An analysis of cross-sectional variations in total household energy requirements in India using micro survey data. *Energy Policy*, *32*(15), 1723-1735.

Parti, M., & Parti, C. (1980). The total and appliance-specific conditional demand for electricity in the household sector. *The Bell Journal of Economics*, 309-321.

Pindyck, R. S., & Rubinfeld, D. L. (2005). *Microeconomics, 6th edition*. Auflage, New Jersey

Poortinga, W., Steg, L., Vlek, C., & Wiersma, G. (2003). Household preferences for energy-saving measures: A conjoint analysis. *Journal of Economic Psychology*, *24*(1), 49-64.

Poudineh, R., & Jamasb, T. (2014). Distributed generation, storage, demand response and energy efficiency as alternatives to grid capacity enhancement. *Energy Policy*, *67*, 222-231.

Puustinen, T. L. M., & Viitanen, K. J. (2015). Infill Development on Collectively Owned Residential Properties: Understanding the Decision-making Process – Case Studies in Helsinki. *Housing, Theory and Society*, *32*(4), 472–498.

Quan, S. J., Economou, A., Grasl, T., & Yang, P. P. J. (2014). Computing energy performance of building density, shape and typology in urban context. *Energy Procedia*, *61*, 1602–1605.

Quan, S. J., Wu, J., Wang, Y., Shi, Z., Yang, T., & Yang, P. P. J. (2016). Urban form and building energy performance in Shanghai neighborhoods. *Energy Procedia*, *88*, 126–132.

Reddy, S., & Painuly, J. P. (2004). Diffusion of renewable energy technologies—barriers and stakeholders' perspectives. *Renewable Energy*, *29*(9), 1431-1447.

Reis, S., Seto, E., Northcross, A., Quinn, N. W., Convertino, M., Jones, R. L., ... & Wimberly, M. C. (2015). Integrating modelling and smart sensors for environmental and human health. *Environmental Modelling & Software*, *74*, 238-246.

Reiss, P. C., & White, M. W. (2005). Household electricity demand, revisited. *The Review of Economic Studies*, *72*(3), 853-883.

Rist, L., Campbell, B. M., & Frost, P. (2013). Adaptive management: where are we now?. *Environmental Conservation*, *40*(1), 5-18.

Rode, P., Keim, C., Robazza, G., Viejo, P., & Schofield, J. (2014). Cities and energy: Urban morphology and residential heat-energy demand. *Environment and Planning B: Planning and Design*, *41*(1), 138–162.

Salisu, A. A., & Ayinde, T. O. (2016). Modeling energy demand: Some emerging issues. *Renewable and Sustainable Energy Reviews*, *54*, 1470-1480.

Sathaye, J., & Murtishaw, S. (2004). Market failures, consumer preferences, and transaction costs in energy efficiency purchase decisions. *Lawrence Berkeley National Laboratory*.

Schleich, J., Klobasa, M., Gölz, S., & Brunner, M. (2013). Effects of feedback on residential electricity demand—Findings from a field trial in Austria. *Energy Policy*, *61*, 1097-1106.

Schultz, P. W. (2001). The structure of environmental concern: Concern for self, other people, and the biosphere. *Journal of Environmental Psychology*, *21*(4), 327-339.

Shin, J. S. (1985). Perception of price when price information is costly: evidence from residential electricity demand. *The Review of Economics and Statistics*, 591-598.

Simon, H. A. (1978). Rationality as process and as product of thought. The American economic review, 68(2), 1-16.

Simon, H. A. (2000). Bounded rationality in social science: Today and tomorrow. Mind & Society, 1(1), 25-39.

Sonderegger, R. C. (1978). Movers and stayers: The resident's contribution to variation across houses in energy consumption for space heating. *Energy and Buildings*, *1*(3), 313–324.

Steadman, P., Hamilton, I., & Evans, S. (2014). Energy and urban built form: An empirical and statistical approach. *Building Research and Information*, *42*(1), 17–31.

Steemers, K. (2003). Energy and the city: density, buildings and transport. *Energy and buildings*, 35(1), 3-14.

Steemers, K., & Yun, G. Y. (2009). Household energy consumption: a study of the role of occupants. *Building Research & Information*, *37*(5-6), 625-637.

Steg, L., & Vlek, C. (2009). Encouraging pro-environmental behaviour: An integrative review and research agenda. *Journal of Environmental Psychology*, *29*(3), 309-317.

Stern, P. C., & Dietz, T. (1994). The value basis of environmental concern. *Journal of Social Issues*, *50*(3), 65-84.

Stone, B., & Norman, J. M. (2006). Land use planning and surface heat island formation: A parcel-based radiation flux approach. *Atmospheric Environment*, *40*(19), 3561–3573.

Stone, B., & Rodgers, M. O. (2001). Urban Form and Thermal Efficiency: *How the Design of Cities Influences the Urban Heat Island Effect*. *Journal of the American Planning Association*, *67*(2), 186–198.

Swan, L. G., & Ugursal, V. I. (2009). Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renewable and Sustainable Energy Reviews*, 13(8), 1819-1835.

Swan, L. G., Ugursal, V. I., & Beausoleil-Morrison, I. (2011). Occupant related household energy consumption in Canada: Estimation using a bottom-up neural-network technique. *Energy and Buildings*, *43*(2–3), 326–337.

Swanson, A. and Plumer, B. (2018, January 23). Trump's solar tariffs are clouding the industry's future. Retrieved from https://www.nytimes.com

Taha, H., Akbari, H., Rosenfeld, A., & Huang, J. (1988). Residential cooling loads and the urban heat island-the effects of albedo. *Building and Environment*, *23*(4), 271–283.

Toffler, A., & Alvin, T. (1980). *The third wave* (Vol. 484). New York: Bantam books.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124-1131.

Urquizo, J., Calderón, C., & James, P. (2017). Metrics of urban morphology and their impact on energy consumption: A case study in the United Kingdom. *Energy Research & Social Science*, 1–14.

Vartholomaios, A. (2017). A parametric sensitivity analysis of the influence of urban form on domestic energy consumption for heating and cooling in a Mediterranean city. *Sustainable Cities and Society*, *28*, 135–145.

Villareal, M. J. C., & Moreira, J. M. L. (2016). Household consumption of electricity in Brazil between 1985 and 2013. *Energy Policy*, *96*, 251-259.

Walker, W. E., Rahman, S. A., & Cave, J. (2001). Adaptive policies, policy analysis, and policy-making. *European Journal of Operational Research*, *128*(2), 282-289.

Weart, S. R. (2008). *The discovery of global warming: revised and expanded edition*. Harvard University Press.

Weber, E. U., & Stern, P. C. (2011). Public understanding of climate change in the United States. *American Psychologist*, *66*(4), 315-328.

Willman, L., & Krarti, M. (2013). Optimization of hybrid distributed generation systems for rural communities in Alaska. *Distributed Generation and Alternative Energy Journal*, *28*(4), 7-31.

Wilson, B. (2013). Urban form and residential electricity consumption: Evidence from Illinois, USA. *Landscape and Urban Planning*, *115*, 62–71.

Wilson, C., & Dowlatabadi, H. (2007). Models of decision making and residential energy use. *Annual Review of Environmental Resources*, *32*, 169-203.

Wong, S. L., Wan, K. K. W., & Lam, T. N. T. (2010). Artificial neural networks for energy analysis of office buildings with daylighting. *Applied Energy*, *87*(2), 551–557.

Yang, J., Rivard, H., & Zmeureanu, R. (2005). On-line building energy prediction using adaptive artificial neural networks. *Energy and Buildings*, *37*(12), 1250–1259.

Yazdanie, M., Densing, M., & Wokaun, A. (2016). The Role of Decentralized Generation and Storage Technologies in Future Energy Systems Planning for a Rural Agglomeration in Switzerland. *Energy Policy*, *96*, 432–445.

Yoo, S. H., Lee, J. S., & Kwak, S. J. (2007). Estimation of residential electricity demand function in Seoul by correction for sample selection bias. *Energy Policy*, *35*(11), 5702-5707.

Ziramba, E. (2008). The demand for residential electricity in South Africa. *Energy Policy*, *36*(9), 3460-3466.