

The Impacts of Household Behaviors and Housing Choice on
Residential Energy Consumption

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Abstract

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Despite efforts made in the past decade to curb excessive energy consumption and the corresponding greenhouse gas (GHG) emissions, both energy consumption and GHG emissions are expected to increase in coming years. Not only does such increasing trends epitomize the escalating, enduring human contribution to global warming, it verifies that our current policies are not working, at least not as well as expected or hoped.

Globally, approximately a quarter of our total energy consumption is in the home, almost as much as in any other sector. Yet an understanding of the processes, determinants, and consequences of household energy consumption remains elusive. Conventional research on residential energy consumption has often applied linear methodologies and overwhelmingly focused on physical attributes of the housing stocks and systems. This approach, therefore, has failed: 1) to provide a coherent perspective of energy consumption processes, and 2) to account for the role of household behaviors. Accordingly, conventional energy policy has been left without the essential understanding of the phenomenon that would allow it to take effective action.

To rectify issues with conventional research and policy, this research applies a non-linear and interdisciplinary approach to household energy consumption as an outcome of housing consumption and choice behaviors. Using data from the latest Residential Energy Consumption Survey, I use a set of Structural Equation Models to estimate the direct, indirect, and total effects of household and housing characteristics on energy use. Outcomes demonstrate that household characteristics have an indirect effect on energy consumption by influencing housing unit attributes, the housing choice effect on energy consumption. That is, a household's choice of housing unit has a permanent effect on the household's energy consumption, as an outcome, up until they relocate. Results of this study show that, accounting for the housing choice effects, the overall effect of household characteristics on energy consumption is almost twice as important as anticipated by conventional research.

This study's findings highlight the role of housing choice and consumption behaviors in shaping residential energy consumption patterns. Energy consumption is expected to increase due to inevitable sociodemographic and economic changes. In addition to investing in improved building efficiencies and technologies, smart energy policies aimed at reducing energy consumption should promote more sustainable housing consumption behaviors and provide better housing choices.

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To my mother, who has always been with me since day one.

To my wife, Manijeh, my pride and joy.

CHAPTER ONE

Introduction

This chapter provides an overview of the significance of residential energy consumption with respect to climate change and energy policy, research and policy issues in these areas, and determinants of residential energy use. Further, by characterizing energy consumption as an outcome of housing choice, consumption, and mobility behaviors, this chapter introduces the interdisciplinary framework that I use in this dissertation to analyze the role of households and housing choice in determining energy use at home. The last section, 'Research frameworks', explains this study's conceptual framework, research hypothesis, questions, and goals, as well as the data and modeling used. Throughout this dissertation, I use both "household" and "housing unit" in their singular form to denote any given household and housing unit.

Why Is Research on Residential Energy Consumption Important?

By 2040, world energy consumption will be 56% higher than its 2010 level (U.S. Energy Information Administration 2013a), despite the existence of several global agreements on significantly reducing greenhouse gases (GHGs) and energy consumption. What current policies have achieved in reducing GHG emissions and energy consumption is small, compared to what is needed to stabilize the changing climate (Drummond 2010; Boswell, Greve, and Seale 2010). Globally, buildings (residential and commercial) consume between 20% and 40% of total energy (Swan and Ugursal 2009; Roaf, Crichton, and Nicol 2004; Norman, MacLean, and Kennedy 2006). Energy use in residential buildings is one of the major sources of carbon dioxide emissions production from cities. In 2013, 22% of the energy consumed and 21% of the CO₂ emissions produced in the U.S. was from the residential sector (U.S. Energy Information Administration 2013b).

About 40 years after the oil crisis of the late 1970s (Meyers and Schipper 1984), the residential sector has once again become prominent in energy policy debates for its impact on climate change (Brounen, Kok, and Quigley 2012). A clear understanding of residential energy consumption is the key constituent of effective energy policy and planning (Hirst 1980; Brounen, Kok, and Quigley 2012). Nevertheless, when it comes to residential energy use, all we know is ‘uncertainty’ (Lutzenhiser et al. 2010, 169). Three principal reasons explain the uncertainties in household energy consumption research and theory, obstructing the clear understanding needed for effective energy policy.

First, the standard ‘traditional’ research has commonly used linear methodologies to analyze energy use in the residential sector, failing to account for its complexities. Household energy consumption patterns are complex socio-technical phenomena (Cramer et al. 1984; Lutzenhiser 1997). However, due to limited ‘programmatic’ or ‘financial’ support, energy research have often been separated between disciplines (Lutzenhiser 1992; Moezzi and Lutzenhiser 2010). Therefore, empirical research on the complexities of the drivers of residential energy consumption is insufficient (Kelly 2011). For a better energy policy, a better understanding of its complexities is needed (Aune 2007; Swan and Ugursal 2009; Hirst 1980).

Second, the current residential energy debate has been overly focused on the housing stock and its technical attributes, underestimating the role of resident households (Brounen, Kok, and Quigley 2012; Kavgic et al. 2010; Lutzenhiser 1993; Kriström 2006). The few residential energy consumption studies account for only a limited set of sociodemographic attributes (O’Neill and Chen 2002), and/or often do not pay attention to the complexities of human behavior (Lutzenhiser 1992). Therefore, many potential social and behavioral constituents of

residential energy consumption (e.g. gender, ethnicity, education, etc.) are yet to be identified.

The complexity of the human role in the energy consumption process makes meaningful interpretation of modeling results rather difficult, which in turn leads to ambiguities and a limited understanding of the role of socioeconomic and behavioral determinants of residential energy use. This issue is partially due to methodological or data deficiencies. As the third issue in residential energy research, lack of publicly available data has intensified both issues in studying residential energy consumption (Min, Hausfather, and Lin 2010; Kavgic et al. 2010; Pérez-Lombard, Ortiz, and Pout 2008; Lutzenhiser et al. 2010; Hirst 1980; Kriström 2006). Methodological approaches lag behind theoretical advances, because the energy data available for quantitative analysis often do not provide socio-cultural information related to energy users (Crosbie 2006).

This prevalent theoretical and methodological uncertainty has often left policy being made on the basis of inefficient conventional speculations. To many planners and policymakers the energy consumed by homes is an invisible resource (Brandon and Lewis 1999; Swan and Ugursal 2009). Most of the research and policy attention on energy and GHG reduction strategies has been granted to transportation (Ewing and Rong 2008). It is startling to see very little work published in planning journals on residential energy consumption.

Many of the determinants of energy use in the residential sector are similar to those of housing consumption behaviors. Socioeconomic characteristics influence households' housing consumption, location choices, mobility behaviors, and energy use. Such simultaneities are inherent, but not made explicit in prior research. For instance, under the free mobility assumption, an increase in household size is likely to be correlated with moving to a bigger home. According to prior research, both bigger homes and larger household sizes correlate

with higher total energy consumption. Nevertheless, using standard linear methodologies, it remains unclear to what extent the two associations are endogenous to each other.

Using a detailed household-level energy consumption dataset, this dissertation aims to address two theoretical and methodological deficiencies in residential energy consumption research. Buildings do not consume energy, per se; rather, consumption energy (and other natural resources) at homes is an outcome of human activities, behaviors, and choices. I study residential energy consumption under the rubric of housing choice, consumption, and mobility behaviors, by characterizing it as a component of consumption of housing services.

Determinants of Residential Energy Consumption

Residential buildings consume energy for space heating and cooling, domestic hot water, and appliances and lighting. Local climatic conditions, housing unit characteristics, home appliances and energy systems, energy price, and household behaviors determine energy consumption in the residential sector (Swan and Ugursal 2009; Shimoda et al. 2007; Pérez-Lombard, Ortiz, and Pout 2008; Hirst, Goeltz, and Carney 1982; Cramer et al. 1984; Yu et al. 2011; Brounen, Kok, and Quigley 2012; Van Raaij and Verhallen 1983a)

In general, the determinants of residential energy use can be categorized into contextual and psychological (behavioral) domains (Wilson and Dowlatabadi 2007). The contextual domain embraces factors such as local climate, energy market, and attributes of the building (including physical attributes and energy system). The behavioral domain take in user characteristics (including sociodemographic, economic, and cultural) that influence energy consumption. From the two domains, this study focuses on the effect of a set of housing attributes (Building Effects) and household characteristics (Household Effects), as illustrated in Figure 1.

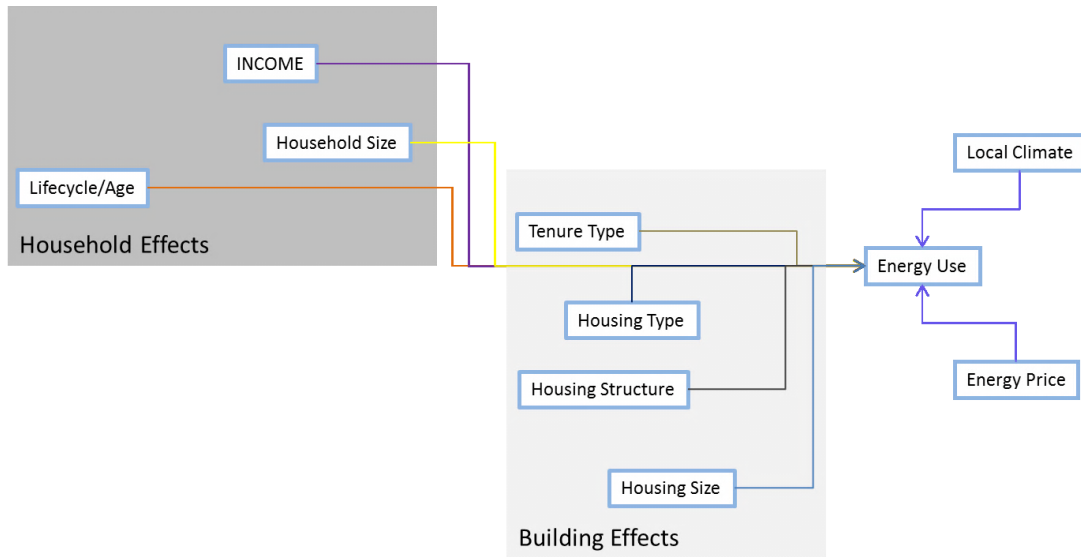


Figure 1. Interactions between selected determinants of residential energy use

Building Effects

Two groups of building characteristics influence residential energy consumption: (1) factors related to energy efficiency of the building (e.g., construction quality, insulation, energy efficiency systems, construction materials, etc.); and (2) physical attributes of the building such as housing type and size. This study focuses on the second group (physical attributes).

- *Housing size*

An increase in size of residential buildings correlates with higher energy consumption at home (Kelly 2011; Brounen, Kok, and Quigley 2012; Ewing and Rong 2008; Kaza 2010; Shimoda et al. 2007).

- *Housing type*

In general, detached dwelling consume significantly more energy (Brounen, Kok, and Quigley 2012; Guerra Santin, Itard, and Visscher 2009; Ewing and Rong 2008; Baxter et al. 1986; Holden and Norland 2005; Santamouris et al. 2007).

- *Housing Age*

Older homes consume more energy (Guerra Santin, Itard, and Visscher 2009; Brounen, Kok, and Quigley 2012; Ewing and Rong 2008; Hirst, Goeltz, and Carney 1982; Santamouris et al. 2007).

- *Tenure type*

The effect of home tenure type on energy consumption has not been well-studied; however, in energy consumption literature ownership seems to be the preferred tenure type over renting (Baxter et al. 1986; Long 1993; Guerra Santin, Itard, and Visscher 2009).

Household Effects

Prior research has reported the role of the following demographic and socioeconomic characteristics on residential energy consumption. I characterize prior research findings under two categories. The first category embraces household lifecycle-related characteristics:

- *Household size and composition*

In general, an increase in household size often correlates with a higher total energy consumption (Kelly 2011; Guerra Santin, Itard, and Visscher 2009; Druckman and Jackson 2008). However, the effect of household size varies by household composition. For example, the presence of children tends to increase energy consumption at home (Van Raaij and Verhallen 1983a; Brounen, Kok, and Quigley 2012).

- *Age of Householder*

Older households are expected to consume more energy (Brounen, Kok, and Quigley 2012; Guerra Santin, Itard, and Visscher 2009; Yamasaki and Tominaga 1997; Tonn and Eisenberg 2007). However, the relationship between household lifecycle is not linear, as the growth rate decreases over time as older households tend to have more energy-efficient behaviors (Fritzsche 1981; Carlsson-kanyama, Lindén, and Eriksson 2005).

The second category of household-related determinants of residential energy consumption include social and economic factors:

- *Income*

Even with similar household characteristics, income positively correlates with energy consumption (Brounen, Kok, and Quigley 2012; Guerra Santin, Itard, and Visscher 2009; Ewing and Rong 2008; Vassileva, Wallin, and Dahlquist 2012; Druckman and Jackson 2008; Kriström 2006; Larson, Liu, and Yezer 2012; O'Neill and Chen 2002; Brandon and Lewis 1999). However, prior research provides additional evidence that suggest the effect of income on energy consumption is more complex than a simple correlation, due to its effect on the housing characteristics (Santamouris et al. 2007; Van Raaij and Verhallen 1983b; Kelly 2011; Steemers and Yun 2009) (Santamouris, et al., 2007).

- *Race and/or Ethnicity*

Energy consumption also varies by race and/or ethnicity (Ewing and Rong 2008; Poyer, Henderson, and Teotia 1997; Poyer and Williams 1993). Similar to income's effect on energy consumption, the effect of racial and/or ethnic status on energy consumption goes beyond direct behavioral correlations (Poyer and Williams 1993). Nonetheless, such differences have not been well studied.

Residential Energy Consumption and Housing Consumption

In addition to their direct effects, household and building characteristics determine energy consumption interactively (Van Raaij and Verhallen 1983a). The processes that influence housing choice and mobility behaviors are also influential in residential energy consumption. Energy consumption within residential buildings can be considered as an outcome of housing choice and consumption behaviors. Residential energy consumption is indirectly correlated with housing consumption and choice behaviors that, in turn, correspond with household

characteristics (e.g. income, size, etc.) and housing market conditions (Ewing and Rong 2008). This is because: “Energy demand by the household is a derived demand – we do not demand energy per se; energy is combined with other goods, typically a capital good [such as home and home appliances], in order to produce (or derive) the services we ultimately wish for.” (Kriström 2006, 96)

Local climate and building characteristics alone cannot provide sufficient information on residential energy consumption. Understanding the role of occupants’ characteristics and behaviors in shaping energy use is essential, especially through its influence on housing characteristics (Steemers and Yun 2009). Dubin & Mcfadden (1984) argue that home energy consumption decisions (e.g., purchase or retrofit decisions on portable appliances, space and water heating decisions, etc.) are often made earlier, when the housing unit is chosen (Dubin and Mcfadden 1984, 350). Therefore, the effect of occupant characteristics on energy consumption is potentially larger than regression estimates as they also determine building characteristics (Guerra Santin, Itard, and Visscher 2009).

For instance, housing consumption behaviors favoring bigger, detached housing types often correlate with particular socioeconomic characteristics. Larger households with higher incomes are more likely to live in detached and bigger homes (Ewing and Rong 2008). According to the reviewed research, all of these characteristics independently correlate with increased energy consumption. However, we do not know to what extent such correlations are endogenous to each other.

Housing Choice, Consumption, and Mobility Behaviors

Residential mobility presents the main opportunity of reestablishing equilibrium between households’ actual consumption of housing-related services and their needs and desires (Rossi 1955; Quigley and Weinberg 1977; Chevan 1971; Mulder 1996). Disequilibria in

housing consumption may ensue due to changes in households' socioeconomic characteristics, or in response to alterations in contextual factors related to the location of residence (Dieleman 2001a; W. A. V. Clark and Onaka 1983a; Oishi 2010).

Households often evaluate the attributes of the bundle of housing services in two groups: (a) the dwelling unit and (b) locational characteristics (Dieleman 2001a). Neighborhood and metropolitan characteristics can influence households' preferences, and therefore stimulate residential mobility (W. A. V. Clark, Deurloo, and Dieleman 2006) and demand for housing (Ioannides and Zabel 2008). Rates of residential mobility also vary substantially among different housing markets (Graves and Regulskka 1982; Vlist et al. 2002; Dieleman, Clark, and Deurloo 2000). Furthermore, proximity to work can foster longer stays in a given residential location (Eluru et al. 2009). However, the effect of locational attributes such as distance to work on residential mobility behaviors are secondary, compared to household- and housing-related inducements (B. A. Lee, Oropesa, and Kanan 1994).

Residential mobility is primarily a demographic event that manifests in geography (White and Mueser 1988), and mobility behaviors are strongly connected with households' socioeconomic characteristics (W. A. V. Clark, Deurloo, and Dieleman 2006; W. A. V. Clark and Dieleman 1996; Simmons 1968). As illustrated in Figure 2, housing choice, consumption, and mobility behaviors form interactions between socioeconomic and contextual domains. Most influential factors fit into individual and community scales (Oishi 2010). In this categorization, individual factors demonstrate household-related determinants of residential relocation, while community-scale factor encompass contextual determinants. To generate mobility behaviors, factors in both categories directly interact with physical characteristics of the dwelling unit, and indirectly interact with each other.

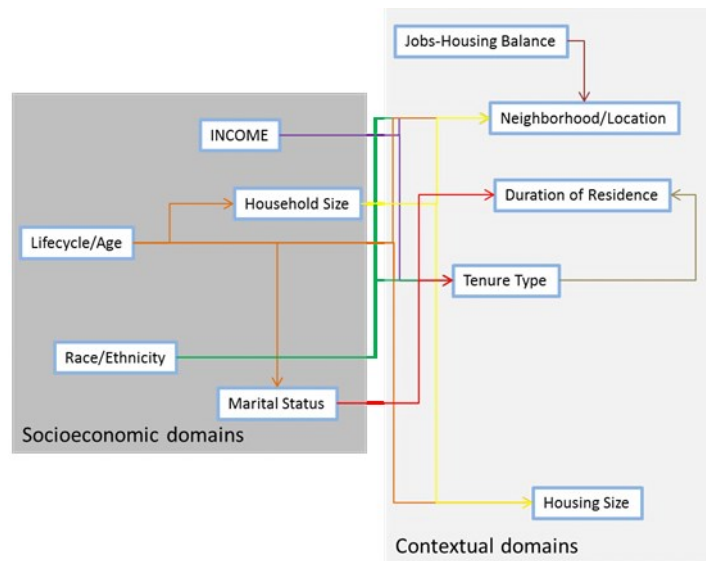


Figure 2. Housing choice, consumption, and mobility behaviors in interactions between contextual and socioeconomic domains

- *Lifecycle/Life Course/Age*

When people are free to move, residential mobility is the adjustment process through which households match their housing needs at different lifecycle stages with their location of residence (Chevan 1971; Simmons 1968; W. A. V. Clark and Dieleman 1996; B. A. Lee, Oropesa, and Kanan 1994). In general, the age of householder is negatively associated with the probability of moving (Boehm and Ihlanfeldt 1986; Landale and Guest 1985; B. A. Lee, Oropesa, and Kanan 1994).

Since the 1990s, lifecycle theories of housing behavior have been criticized for being ‘normative’ and ‘deterministic’, and gradually substituted by the more flexible ‘life course’ approach, (van Ham 2012; W. A. V. Clark and Dieleman 1996; Kulu and Milewski 2007; Geist and Mcmanus 2008; Bailey 2008; W. A. V. Clark and Davies Withers 2007). The life course approach envisions a household career as a sequence of parallel and interrelated transitions of life events (e.g., marriage, having children, work and education, etc.) that influence housing choice and mobility decisions (W. A. V. Clark and Dieleman 1996; van Ham 2012; W. A. V. Clark and Davies Withers 2007). Life course trajectories are linked with housing needs

and household preferences, such as space needs, dwelling characteristics, or residential location and amenities (Mudler and Hooimeijer 1999).

- *Household size and composition*

Household size and composition correlate with housing consumption behavior and its corresponding effect on mobility behaviors (Beguin 1982; Boehm 1982; W. A. V. Clark, Deurloo, and Dieleman 1984; Chevan 1971). Changes in family composition (e.g. presence of children) often imply space requirements and desires, and thus influence mobility behaviors (W. A. V. Clark and Dieleman 1996; Chevan 1971; W. A. V. Clark and Huang 2003).

- *Race or Ethnicity*

While many of the mobility stimuli operate similarly among racial/ethnic groups, the magnitude and form of the influence for each determinant of mobility varies across racial groups (Scott J South and Deane 1993; Scott J. South and Crowder 1998a; Crowder, South, and Chavez 2006; Rossi and Weber 1996; Boehm and Ihlanfeld 1986).

- *Income*

The association between income and residential mobility has been discussed by several researchers (Boehm and Ihlanfeld 1986; Boehm 1982; Chan 2001; W. A. V. Clark 2007; Graves and Regulska 1982; Scott J. South and Crowder 1998b), and remains of high importance, especially with regard to housing supply and demand. An increase in income can have varying effects on mobility based on tenure type and household characteristics (Boehm 1982; Boehm and Ihlanfeld 1986). The association between income and mobility seems to be consistent with households in racial and ethnic groups.

- *Tenure Type*

Along with lifecycle effects, home tenure status is the one of the few background players in the housing consumption and mobility process that has a direct and significant influence on

household behaviors (Alden Speare 1974; W. A. V. Clark, Deurloo, and Dieleman 1984; S J South and Crowder 1997). For example, homeownership has been shown to significantly reduce mobility (W. A. V. Clark and Huang 2003; B. A. Lee, Oropesa, and Kanan 1994; Alden; Speare and Goldscheider 1987).

- *Duration of Residence*

Longtime residence at a location is expected to reduce the chances of moving (B. A. Lee, Oropesa, and Kanan 1994). Nonetheless, interlinked unobserved factors may influence both the decision to move and the duration of residence. Many of the exogenous socioeconomic or contextual characteristics that increase mobility rates are motives for shorter stays at a given residence. For example, smaller houses increase the propensity of shorter stays.

Research Framework

This research aims to advance policy and research approaches to residential energy consumption by overlaying the two processes of residential energy use and residential mobility and housing consumption behaviors (Figure 3). I characterize residential energy consumption as an outcome of a set of interactions and mediations between multiple housing- and household-related characteristics: interactions and mediations that stimulate housing choice, consumption, and mobility behaviors. Studying the interactions and mediations between determinants of energy use with this research framework provides insights that, if not controversial, are novel for energy policy.

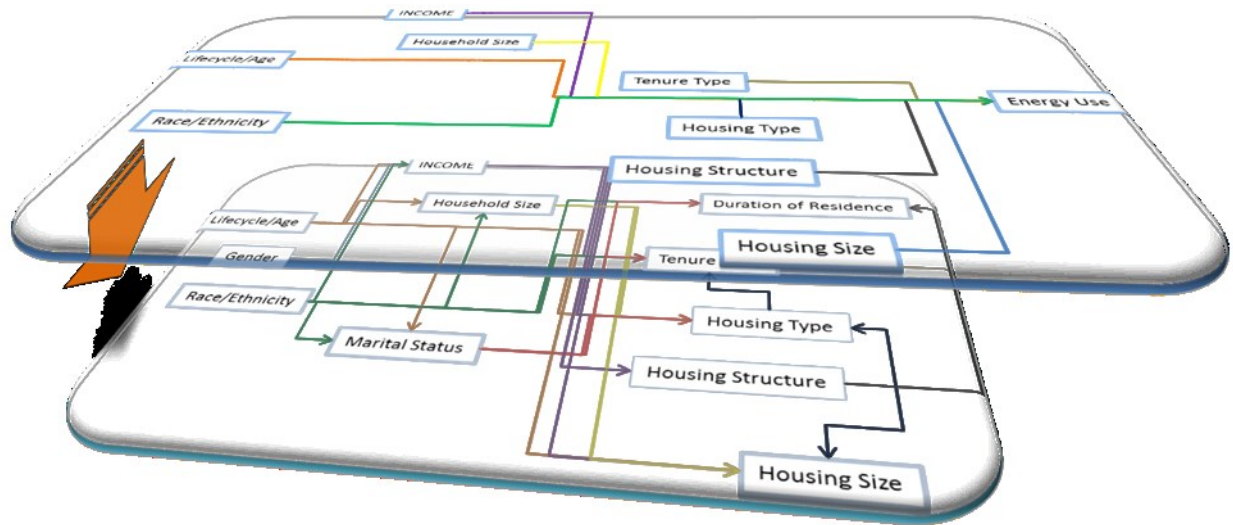


Figure 3. Overlaying residential energy use and mobility processes

The Conceptual Model

The conceptual model of this research comprises interactions from three sets of variables: 1) household characteristics, 2) housing unit characteristics, and, as outcome, 3) energy consumption (Figure 4). Based on the conceptual model, the research hypothesis is that the household effect on energy consumption is much larger than what is anticipated in conventional research. Under this conceptualization, the impact of households on energy consumption is twofold: (1) a direct impact that represents energy consumption behaviors, and (2) an indirect impact through choice of housing unit characteristics.

Housing unit characteristics, in turn, generate a direct impact on the energy use index, which has been partially deliberated in prior research. However, such a direct impact is a cumulative of households' housing choice behaviors and building effects. That is, households that choose bigger single-family housing are also likely to be more liberal in their use of either additional or high-end home appliances that better matches their housing characteristics (e.g. AC, fireplaces, hot tubs, etc.). Beyond the direct building effects, such housing unit-related behaviors will be reflected in overall energy consumption. Previous studies have often failed to distinguish these indirect effects. Therefore, I suspect that the total effect of the

housing unit (reflecting the combination of indirect and direct effects) may embrace a spurious effect that is not due to housing characteristics. The conceptual model in my dissertation will allow us to account for both direct and indirect effects of housing units.

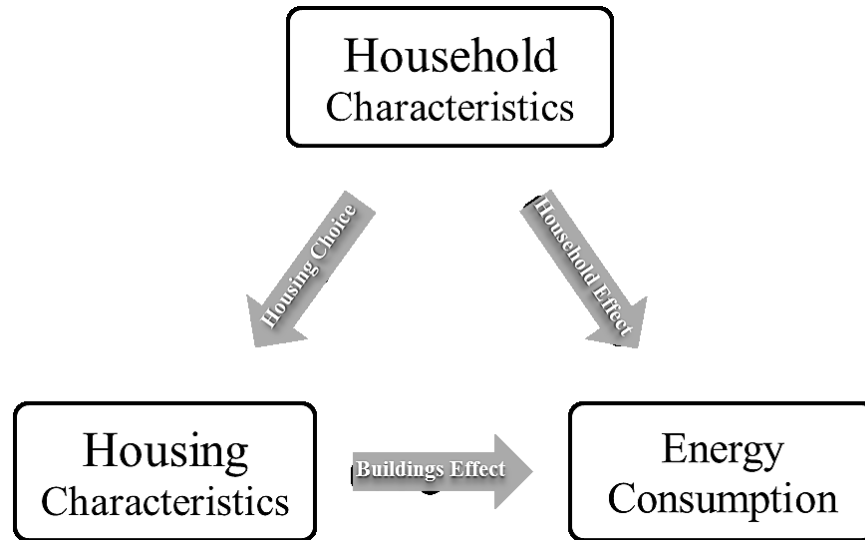


Figure 4. The conceptual model characterizing energy consumption as an outcome of interactions between socioeconomic and housing unit characteristics

Research Questions

The corresponding research questions are:

- i. How do the direct, indirect, and total effects of households' socioeconomics and housing characteristics on energy consumption differ?
- ii. How are household and housing characteristics related in determining residential energy consumption?

Research Goals

Through this research, I seek to achieve two main ensuing goals:

- 1) To improve the current state of knowledge about the drivers of residential energy use by:
 - a) Isolating the direct, indirect, and total impacts of buildings and households on energy use.
 - b) Examining the roles of additional household- and housing-related variables on residential energy consumption – variables that have been identified as

being influential in housing consumption research, but neglected in residential energy use research.

- 2) To transform urban energy policy and planning by introducing a novel outlook that connects residential energy use to underlying housing choice, consumption, and mobility behaviors.

Data

To address these research goals and this hypothesis, I use the newly released microdata from the 2009 Residential Energy Consumption Survey (RECS) (U.S. Energy Information Administration 2013c). RECS is a national sample survey that collects energy-, housing-, and household-related data, sponsored by the U.S. Energy Information Administration (EIA). The 2009 microdata embodies information from 12,083 households selected at random using a complex multistage, area-probability sample design. The EIA asserts that RECS is “the only survey that provides reliable, accurate and precise trend comparisons of energy consumption between households, housing types, and areas of the country” (U.S. Energy Information Administration 2011).

Modeling

I use Structural Equation Modeling (SEM) to estimate the effects of selected variables on energy consumption under a specific covariance structure that represents the proposed conceptual model. The structural equation model implies a covariance structure between the observed variable (Hox and Bechger 2007), representing a series of structural equations (Byrne 1998) to evaluate the validity of a substantive theory with empirical data (Lei and Wu 2007). Use of SEM offers several benefits over traditional regression techniques (Byrne 1998; Lei and Wu 2007; Dion 2008). However, due to the importance of certain modeling assumptions (e.g., multivariate normality, continuous data), I employed an Asymptotically Distribution-Free (ADF) estimator, robust WLS estimation method, which is able to

accommodate non-normally distributed and/or ordered categorical data (Finney and DiStefano 2006; Skrondal and Rabe-Hesketh 2005).

CHAPTER TWO

Introduction

This chapter provides a comprehensive review of the literature on the two substantive areas of research overlaid in this research. The first section illustrates information about energy consumption in the residential sector, in the U.S. and globally, and develops an in-depth discussion on the inefficiencies of residential energy research and policy. Determinants of residential energy consumption based on prior research are discussed. The second section is a literature review on housing choice, consumption, and mobility behaviors, which includes motivations, limitations, and household- and housing-related determinants.

Energy Consumption in the Residential Sector

According to the International Energy Outlook 2013 (IEO2013), by 2040, world energy consumption will be 56% higher than its 2010 level, most of which is due to socioeconomic transformations in developing countries (U.S. Energy Information Administration 2013a). This increase is expected to occur despite the existence of several global agreements within the past few decades on significantly reducing greenhouse gases (GHGs) and energy consumption (e.g. the Kyoto Protocol, adopted in December 1997 and entered into force in February 2005). What we have achieved with current policies (which are often derived from traditional approaches) in GHG emissions and energy consumption reductions is limited, compared to what is needed to stabilize the climate (Drummond 2010; Boswell, Greve, and Seale 2010).

Globally, buildings (residential and commercial) consume between 20% and 40% of total energy (Swan and Ugursal 2009; Roaf, Crichton, and Nicol 2004; Norman, MacLean, and Kennedy 2006), exceeding the industrial and transportation sectors (Pérez-Lombard, Ortiz, and Pout 2008). About 20% (Brounen, Kok, and Quigley 2012; U.S. Energy Information Administration 2013a) to 30% (Van Raaij and Verhallen 1983a; Hitchcock 1993) of total

energy demand is for domestic (residential) use. Energy use in residential buildings is one of the major sources of carbon dioxide emissions production from cities. In 2013, 22% of the energy consumed and 21% of the CO₂ emissions produced in the U.S. came from the residential sector (Figure 5 and Figure 6), both of which are expected to slightly diminish in their share to 20% and 19%, respectively, due to faster increases in industrial and commercial energy consumption (U.S. Energy Information Administration 2013b).

Technological improvements are expected to diminish growth rates in residential and transportation energy use. Since developed countries have greater access to up-to-date technologies, energy consumed in the residential buildings is likely to increase at a slower pace in developed countries, with an average of 14% in developed and 109% in developing countries (Figure 7) (U.S. Energy Information Administration 2013a). If current laws and regulations stand, by 2040 residential energy consumption will face a 2.3% increase in the U.S. (Figure 8) (U.S. Energy Information Administration 2013b).

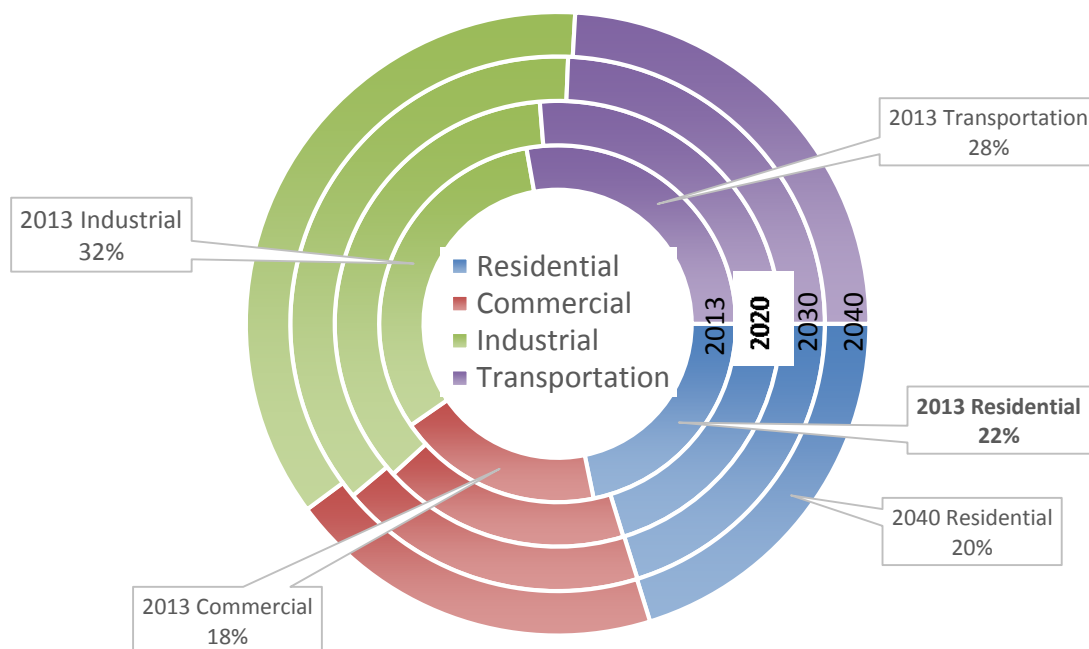


Figure 5. U.S. Energy Consumption by Sector, 2013, 2020, 2030, and 2040. Data source: (U.S. Energy Information Administration 2013b)

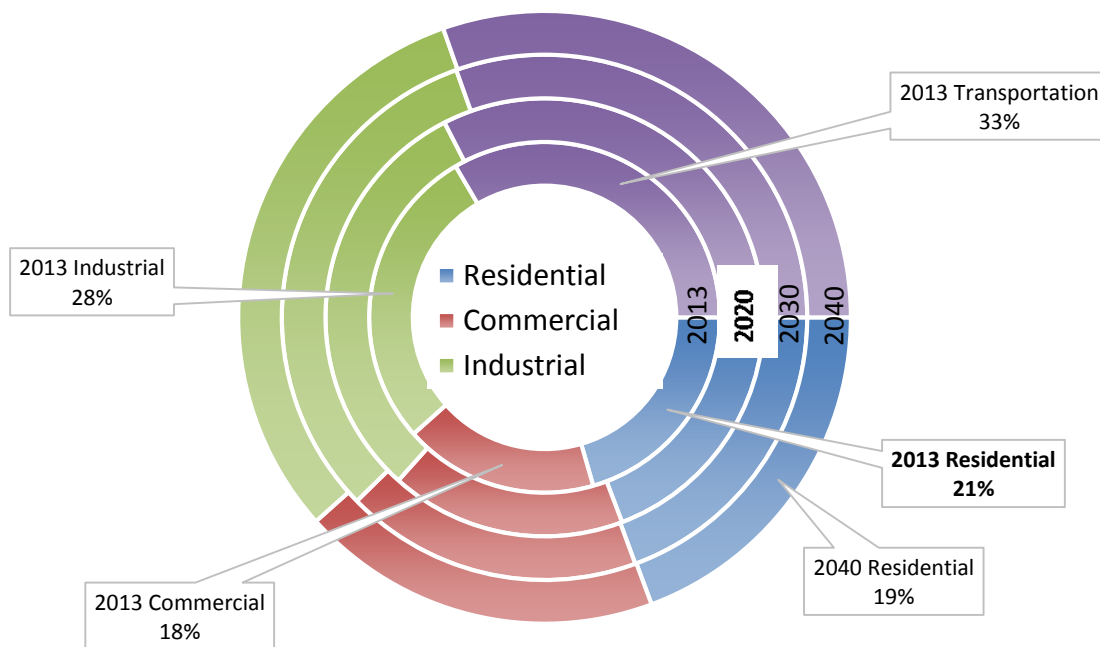


Figure 6. U.S. CO₂ Emissions by Sector, 2013, 2020, 2030, and 2040. Data source: (U.S. Energy Information Administration 2013b)

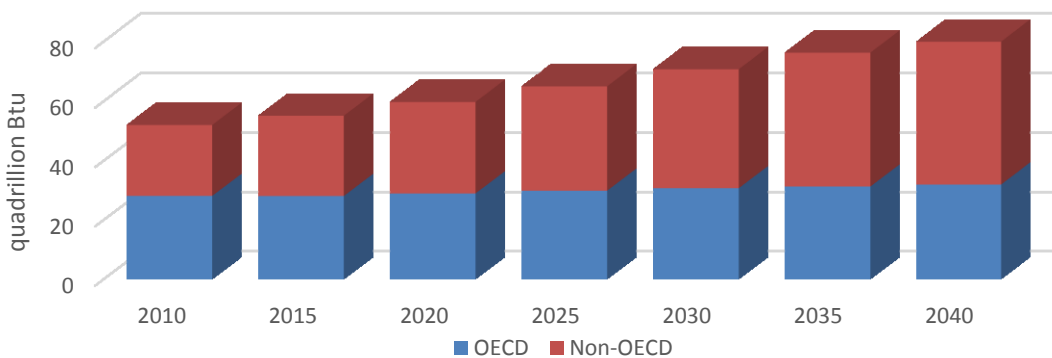


Figure 7. World residential sector delivered energy consumption, 2010-2040. Data Source (U.S. Energy Information Administration 2013a)

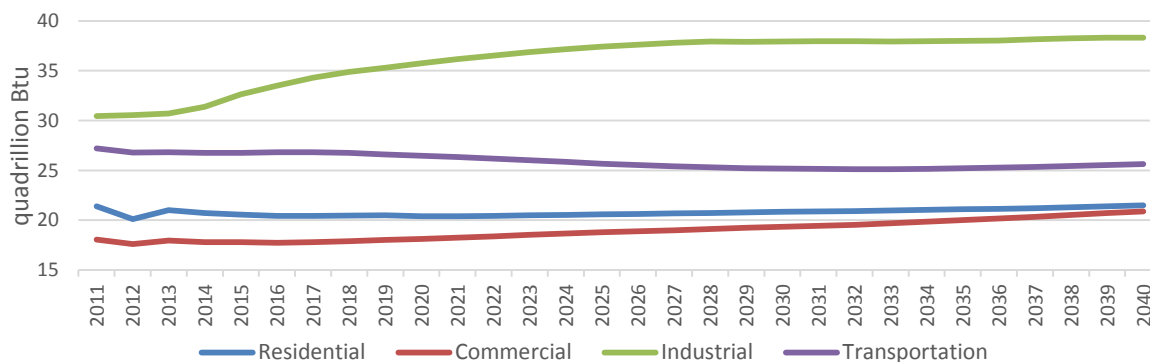


Figure 8. U.S. Energy Consumption Projection by Sector. Data Source: (U.S. Energy Information Administration 2013b)

Back in the 80s, most of the energy use in residential buildings was for heating – home heating 75% and water heating 15% (Van Raaij and Verhallen 1983a). Currently, according to U.S. Energy Information Administration (2013), due to the expected increase in average global temperature, much of the increase in residential energy consumption will be for space cooling, refrigeration and miscellaneous electric loads (Figure 9).

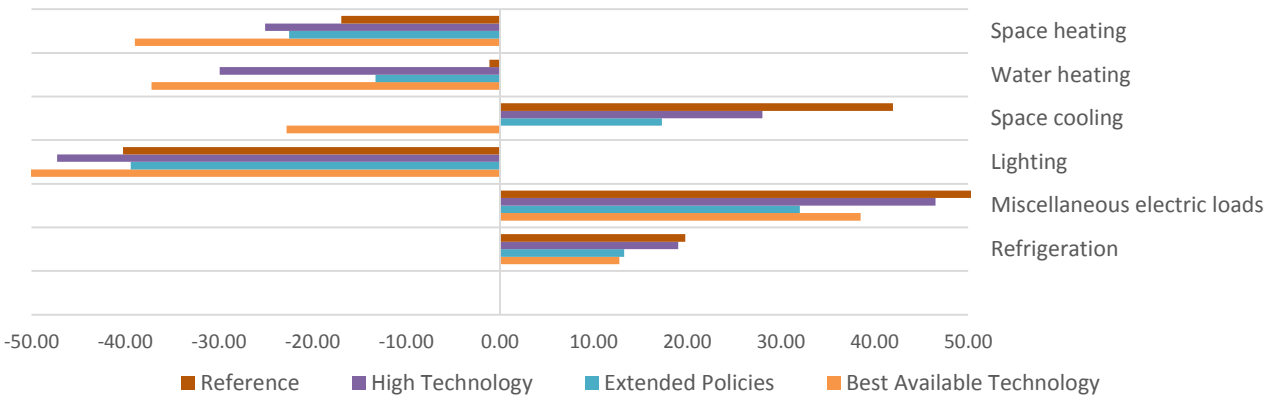


Figure 9. Percent change in U.S. residential delivered energy consumption for selected end uses under four scenarios, 2011-2040. Reference scenario is when current laws and regulations remain unchanged. Data Source: (U.S. Energy Information Administration 2013d)

About 40 years after the oil crisis of the late 1970s (Meyers and Schipper 1984), the residential sector has once again become prominent in energy policy debates for its impact on climate change (Brounen, Kok, and Quigley 2012). Nevertheless, to many consumers (households), researchers, and policymakers, the energy consumed at homes has become an invisible resource (Brandon and Lewis 1999). The state of knowledge about household energy use could be summarized in one word: “uncertainty” (Lutzenhiser et al. 2010, 169). This prevalent theoretical and methodological uncertainty has often left policy being made on the basis of inefficient conventional speculations, such as the following statement from Glaeser and Kahn (2010):

“If the urban population lived at higher population density levels closer to city centers in regions of the country with warmer winters and cooler summers in areas whose electric utilities used less coal for producing power, then household [energy consumption and] greenhouse gas production would be lower.” (Glaeser and Kahn 2010, 416)

A clear understanding of residential energy consumption is the key constituent of effective energy policy and planning (Hirst 1980; Brounen, Kok, and Quigley 2012). Three principal reasons explain the uncertainties in household energy consumption research and theory and obstruct the clear understanding needed for effective energy policy. First, standard “traditional” research has commonly used linear methodologies to analyze energy use in the residential sector, failing to account for its complexities – I characterize this methodological deficiency as a ‘depth’ issue. Second, the current residential energy debate has been overly focused on the housing stock and its technical attributes, underestimating the role of the behaviors of residences’ households’ – I characterize this inclusiveness deficiency as a ‘breadth’ issue. In addition, a lack of publicly available data has intensified both the depth and breadth issues in studying residential energy consumption.

i. Complexities of Residential Energy Consumption: Depth Issue

A set of complex interactions between multiple physical and behavioral factors determines the use of energy in homes (Cramer et al. 1984), and understanding and theorizing its processes and repercussions “is a far from straightforward matter” (Lutzenhiser 1997, 77). Moreover, due to limited ‘programmatic’ or ‘financial’ support, research on energy consumption has often progressed partially within disciplinary boundaries and methodologies (Lutzenhiser 1992; Moezzi and Lutzenhiser 2010). Household energy consumption patterns are complex socio-technical phenomena. However, energy research have often been separated between disciplines. To better understand energy consumption, both (i.e., social and technical) dimensions need to be integrated (Hitchcock 1993). Nevertheless, the lack of profound interdisciplinary approaches to the study of energy system complexities has resulted in a no more than partial understanding of the determinants and consequences of energy consumption (Lutzenhiser 1997; Lutzenhiser 1994).

The impact of household and building characteristics on energy consumption often varies by energy source (Brounen, Kok, and Quigley 2012), between different regions (Min, Hausfather, and Lin 2010; Van Raaij and Verhallen 1983a), among households (Guerra Santin, Itard, and Visscher 2009; Vassileva, Wallin, and Dahlquist 2012; Kaza 2010), and by housing (Brounen, Kok, and Quigley 2012; Guerra Santin, Itard, and Visscher 2009; Ewing and Rong 2008; Baxter et al. 1986; Holden and Norland 2005; Santamouris et al. 2007; Costa and Kahn 2011). Moreover, there are indirect effects in interactions between households and housing unit characteristics (Ewing and Rong 2008; Santamouris et al. 2007; Van Raaij and Verhallen 1983a; Steemers and Yun 2009), which have been commonly overlooked. For a more comprehensive understanding of residential energy consumption we need to study both the direct and the indirect effects (Steemers and Yun 2009).

Yet linear¹ analytical methodologies have been a research standard in understanding domestic energy consumption. The assumption of linearity (where the dependent variable is a linear function of independent variables) and the difficulty to ascertain any causal interpretations (i.e. the correlation vs. causation dilemma) are major downsides of traditional methodologies, such as ordinary regression models (Kelly 2011).

“Household energy consumption is not a physics problem, e.g., with stable principles across time and place, conditions that can be clearly articulated, and laboratory experiments that readily apply to real world.” (Moezzi and Lutzenhiser 2010, 209)

As a consequence of the predominant assumption of linearity in energy consumption research, “the present [conventional] energy policy still conveys a ‘linear’ understanding of

¹ I use the notion of ‘linearity’ in contrast to ‘nonlinearity’ in complex system analysis. Nonlinearity means that a systems behavior cannot be expressed as a sum of the individual behaviors of its constituents. In most complex systems, the multiplicity of causal links form a more complicated identity for the system than a single chain. Therefore, a complex system encompasses an ‘intricate’ graph of causal networks, where outputs are not proportional to the inputs through the whole range of the inputs (MacKay 2008; Phillips 2003).

the implementation of technology” (Aune 2007, 5463) , while aggregate regression models (based on average statistics) cannot explain the complexities of household-level energy consumption (Kelly 2011).

For better energy policies, a better understanding of the complexities of its use is needed (Aune 2007; Swan and Ugursal 2009; Hirst 1980). However, empirical research on the complexities of residential energy consumption drivers is insufficient (Kelly 2011). There is a need for further empirical studies exploring these complexities. In addition, the disciplinary research in this area has proven that residential energy use behaviors can be characterized (to different extent) under decision theories from different research disciplines (Wilson and Dowlatabadi 2007). There is therefore a need for more interdisciplinary research. Not only does interdisciplinarity research integrate different energy consumption theories, it also helps to reveal more dimensions of the complexities involved in household energy use.

ii. Socioeconomic and Behavioral Determinants: Breadth Issue

Traditionally, the debate on residential energy conservation has neglected the role of occupants’ behaviors by excessively focusing on technical and physical attributes of the housing unit (Brounen, Kok, and Quigley 2012; Kavgic et al. 2010; Lutzenhiser 1993; Kriström 2006). Since the early 1990s, energy research and policy have primarily concentrated either on the energy of supply or the efficiency of buildings, neglecting social and behavioral implications of energy demand (Lutzenhiser 1992; Aune 2007; Pérez-Lombard, Ortiz, and Pout 2008; Lutzenhiser 1994; Brounen, Kok, and Quigley 2012). Engineering and economic approaches underestimate the significance of occupant lifestyles and behaviors (Lutzenhiser 1992).

“Engineers and other natural scientists continue to usefully develop innovative solutions to the question of “how we can be more efficient?” However their work does not

answer the question “why are we not more energy-efficient, when clearly it is technically possible for us to be so?” (Crosbie 2006)

In most energy demand studies, only a limited set of socio-demographic attributes are involved (O’Neill and Chen 2002). Even psychological models often do not pay attention to the complexity and ‘dynamic behavior of human groups’ (Lutzenhiser 1992). Of the studies that have accounted for social and cultural factors, on the other hand, most have overlooked the importance of housing characteristics in determining energy consumption (Lutzenhiser 1997), due to methodological or data deficiencies. For example, Hirst, Goeltz and Carney (1982) reported that demographic factors such as number of children and household income are less important in determining residential energy use (Hirst, Goeltz, and Carney 1982).

The complexity of the human role in the energy consumption process makes meaningful interpretation of modeling results rather difficult, which in turn leads to ambiguities and a limited understanding of the role of socioeconomic and behavioral determinants of residential energy use. For example, Yu et al. (2011) found that occupants’ socioeconomic characteristics indirectly influence their energy consumption by influencing their energy consumption behaviors. From this point, however, they suggest that because the influence of socioeconomic factors on energy consumption are reflected in the effect of occupant behaviors, “there is no need to take them into consideration when identifying the effects of influencing factors” (Yu et al. 2011, 1409). Kriström (2006) suggested that “any firm conclusions about household behaviour must be cautioned beyond the usual caveats” (Kriström 2006, 95); a suggestion that can be taken seriously to avoid such misinterpretations.

It is clear that in evaluating residential energy conservation programs, both housing and occupant behaviors need to be taken into account (K. E. Clark and Berry 2007). Due to its complexities, investigating the policy implications of behavioral determinants of residential energy consumption has received little attention in prior research (Brounen, Kok, and

Quigley 2012). Yet, for a more effective energy and carbon reduction policy, policy-makers need to understand variations in energy consumption among households (Druckman and Jackson 2008; Brounen, Kok, and Quigley 2012). Incorporating more sociodemographic attributes could contribute to more flexible, complete, and credible futuristic and historic models of energy consumption (O'Neill and Chen 2002).

Role of Households

Buildings do not consume energy, per se, and residential energy demand is driven by human activity. Despite improving energy efficiency in buildings, energy consumption has continued to grow globally (Ewing and Rong 2008; Pérez-Lombard, Ortiz, and Pout 2008). Future increases in residential energy consumption due to (future) demographic changes, such as income growth and aging, can almost offset the amount of energy conserved by improving the energy efficiency of buildings (Brounen, Kok, and Quigley 2012). Households have different behavioral patterns of energy consumption and should therefore be targeted with different policies (Van Raaij and Verhallen 1983b). However, a clear understanding of the magnitude of resident household effect on energy consumption still remains elusive (Guerra Santin, Itard, and Visscher 2009).

Several recent studies suggest that variation in household energy use is still significant, even after controlling for building characteristics and local climate (Guerra Santin, Itard, and Visscher 2009; Vassileva, Wallin, and Dahlquist 2012; Lutzenhiser 1992). Household energy consumption and conservation behaviors vary systematically by sociodemographic and economic characteristics, and among cultures and lifestyles (Lutzenhiser 1992; Kaza 2010; Wilhite et al. 1996). However, due to different preferences, energy consumption can fluctuate among household with similar characteristics (Vassileva, Wallin, and Dahlquist

2012; Kriström 2006), which can be an indication to households' 'standard of living' (Joyeux and Ripple 2007) and/or 'life style' (Lutzenhiser 1992).

iii. Data Absence

A major problem in residential energy consumption research is that “the data do not stand up to close scrutiny”(Kriström 2006, 96). Although within the past two decades the role of households in energy consumption has been paid more attention, methodological approaches lag behind theoretical advances, partly because data used for quantitative analysis often do not provide socio-cultural information related to energy users (Crosbie 2006). The absence of publicly available high-resolution energy consumption data (specially, spatially explicit data) has hindered development of effective energy research and policy (Min, Hausfather, and Lin 2010; Kavgic et al. 2010; Pérez-Lombard, Ortiz, and Pout 2008; Lutzenhiser et al. 2010; Hirst 1980).

Even though relevant data are being regularly collected by different organizations, such data sources do not often become publicly known (Hirst 1980). Conventional wisdom and modeling practices of energy consumption are often based on “averages” derived from aggregated data (e.g. average energy consumption of an appliance, a housing type, a car, etc.), which do not explicitly reflect human choice of housing and other energy consumptive goods (Lutzenhiser and Lutzenhiser 2006).

Determinants of Residential Energy Consumption

The residential sector consumes secondary energy in major end-use groups such as space heating and cooling, domestic hot water, and appliance and lighting. Energy use in these groups is a function of local climate, the housing unit, home appliances, energy control systems, energy markets, and household characteristics and behaviors (Swan and Ugursal 2009; Shimoda et al. 2007; Pérez-Lombard, Ortiz, and Pout 2008; Hirst, Goeltz, and Carney

1982; Cramer et al. 1984; Yu et al. 2011; Brounen, Kok, and Quigley 2012; Van Raaij and Verhallen 1983a) (Figure 10).

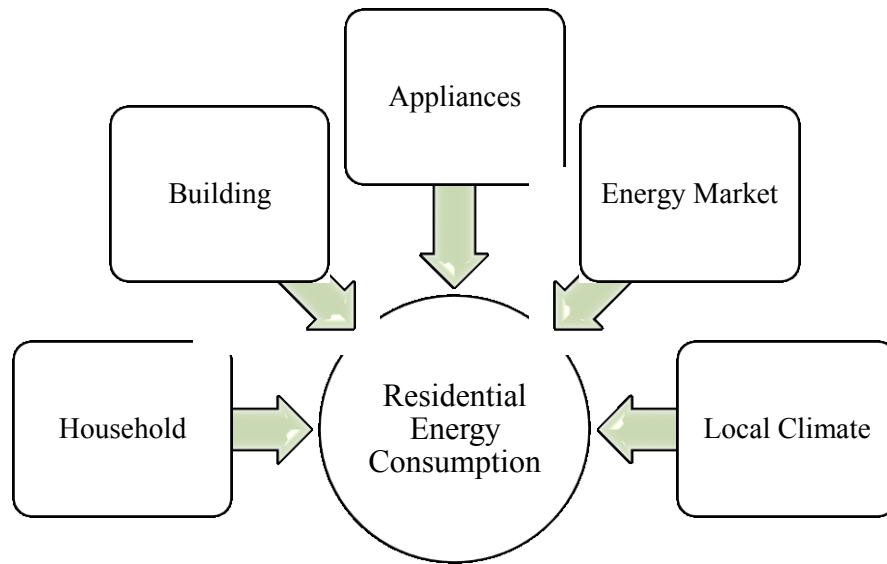


Figure 10. Determinants of Residential Energy Consumption

Van Raaij and Verhallen (1983) proposed one of the earliest models of residential energy consumption, picturing its complexities. Their model, the Behavioral Model, demonstrated energy consumption as the outcome of interactions among multiple groups of household- and housing-related variables, energy-related behaviors and attitudes, energy price and policies and local climate (Van Raaij and Verhallen 1983a). In general, determinants of residential energy use can be categorized into contextual and psychological (behavioral) domains (Wilson and Dowlatabadi 2007). The contextual domain embraces factors such as local climate, energy market, and attributes of the building (including physical attributes and energy system). The behavioral domain take in user characteristics (including sociodemographic, economic, and cultural) that influence energy consumption. From the contextual and behavioral domains, this study focuses on a set of housing- and household-related characteristics.

Household Effects

I characterize prior research findings about household effects on energy consumption under two categories: (1) household lifecycle-related, and (2) social and economic factors.

Lifecycle-related Factors

Similar to the consumption of other housing services, energy use leans towards change over the family lifecycle stages (O'Neill and Chen 2002; Lutzenhiser 1992; Brounen, Kok, and Quigley 2012). Household lifecycle-related characteristics, such as marital status, size, and composition, have a direct effect on energy use behaviors (Van Raaij and Verhallen 1983a).

- *Household size and composition*

Household size and composition are important determinants of energy consumption in residential buildings (O'Neill and Chen 2002; Kaza 2010; Kelly 2011; Brounen, Kok, and Quigley 2012). Kelley (2011) found household size to have the largest impact on energy consumption, among all socioeconomic factors (Kelly 2011). In general, an increase in household size often associates with a higher total energy consumption (Kelly 2011; Guerra Santin, Itard, and Visscher 2009; Druckman and Jackson 2008). However, small households have higher per-capita energy consumption (O'Neill and Chen 2002) and are therefore penalized in their energy expenditure, primarily due to their inability to maximize sharing (Ironmonger, Aitken, and Erbas 1995; Druckman and Jackson 2008).

However, the impact of household size varies by household composition (e.g. number of children and adults, sex of household members, etc.). For example, the presence of children tends to increase energy consumption at home (Van Raaij and Verhallen 1983a; Brounen, Kok, and Quigley 2012). The number of adults has a much larger influence on total energy use than does the number of children (Hirst, Goeltz, and Carney 1982).

- *Householder Age*

Householder age is a proxy indicator of the household lifecycle, and the changes that occur in household size and composition. Age predicts residential energy consumption behaviors as well as do income and dwelling type (Carlsson-kanyama, Lindén, and Eriksson 2005). In addition, attitudes toward the use of appliances and residential locations differ as households lifecycle changes, and so does energy consumption at home (Yamasaki and Tominaga 1997). Lutzenhiser (1992 & 2006) divides the recognizable US lifestyles or cultural forms characterized by different energy consumption behaviors into 5 common types², of which age is the principal constituent (Lutzenhiser 1992; Lutzenhiser and Lutzenhiser 2006).

In general, older households are expected to consume more energy (Brounen, Kok, and Quigley 2012; Guerra Santin, Itard, and Visscher 2009; Yamasaki and Tominaga 1997; Tonn and Eisenberg 2007). However, the relationship between household lifecycle is not linear, as the growing trend decreases over time. Overall, middle-aged, married households with children are the largest energy consumers, compared with households at earlier and later lifecycle stages (Fritzsche 1981). Older households tend to have more energy efficient behaviors in use of laundry and bathing (Carlsson-kanyama, Lindén, and Eriksson 2005).

Social and Economic Factors

Social and economic indicators like income, education, and employment influence household energy consumption (Van Raaij and Verhallen 1983a). Yet, “empirical studies are yet to converge on the relationship between socio-economic variables” (Kriström 2006, 108). Of social and economic factors, income and elasticity to energy price have received the most research attention.

² The 5 groups include: retired working class couples, middle-aged couples, low income rural families, suburban executive families, and young urban families (Lutzenhiser 1992; Lutzenhiser and Lutzenhiser 2006).

- *Income*

Consistent across different studies, the role of income is prominent in determining energy consumption. Even with similar household characteristics, energy consumption varies substantially among households with different incomes, with income being positively correlated with energy consumption (Brounen, Kok, and Quigley 2012; Guerra Santin, Itard, and Visscher 2009; Ewing and Rong 2008; Vassileva, Wallin, and Dahlquist 2012; Druckman and Jackson 2008; Krström 2006; Larson, Liu, and Yezer 2012; O'Neill and Chen 2002; Brandon and Lewis 1999).

Distribution of energy consumption is skewed, with the lowest quartile of households consuming significantly less than the top quartile households (Lutzenhiser and Lutzenhiser 2006; Colton 2002). However, prior research provides additional evidence that suggest the effect of income on energy consumption is more complex than a simple correlation. Although the poor use less energy, they have a relatively smaller opportunity of reducing their energy use, compared with high-income consumers. That is because low-income households are more likely to reside in buildings that are older and have poor envelop conditions (Santamouris, et al., 2007).

“The better-off spend 40 percent more on natural gas for home heating, because their dwellings are larger and the energy price constitutes a relatively small proportion of their budget. The poor in the U.S.A. are generally older, have small families (children have left home), have a lower educational level, are more often black; their families are more often incomplete (husband or wife absent) and they do not own but rent their homes. Their homes are generally of a poor quality, with a poor insulation and a less efficient heating system. They conserve energy as much as they can, but their poorly insulated home is energy-wasting. Low-income earners cannot easily reduce their energy use any further.”
(Van Raaij and Verhallen 1983a)

Part of income's effect on energy consumption is indirect. Only a few studies have pointed to such a distinction in the effect of income on energy consumption. Kelly (2011) found that

both the direct and total effects of income on household energy use are positive (Kelly 2011). The direct effect is, however, small, and income's main effect on energy consumption is through housing size and type (Steemers and Yun 2009).

While they live in newer and more efficient homes, higher income households pay significantly (160%) more for energy (Santamouris et al. 2007). Prior research suggest that energy demand is often not price-elastic and price elasticity is different for different incomes and racial/ethnic groups (Kriström 2006; Reiss and White 2005; Poyer and Williams 1993; Nesbakken 1999). Anker-Nilssen 2003 argues that when income levels pass a certain threshold, households' energy consumption becomes less sensitive to energy prices: "With rising real income, consumption becomes an act of pleasure beyond satisfying basic needs" (Anker-Nilssen 2003, 194).

- *Race and/or Ethnicity*

Energy consumption also varies by race and/or ethnicity (Ewing and Rong 2008; Poyer, Henderson, and Teotia 1997; Poyer and Williams 1993). Similar to income's effect on energy consumption, the effect of racial and/or ethnic status on energy consumption is beyond solely direct behavioral correlations. Race and/or ethnicity are closely connected with income, so at least part of this effect mediates through income disparities. For example, Poyer and Williams (1993) found that Blacks are more sensitive to fluctuations in energy price (Poyer and Williams 1993). Nonetheless, such differences have not been well studied.

Building Effects

The importance of housing unit characteristics on determining residential energy consumption is widely accepted (Guerra Santin, Itard, and Visscher 2009). There are two groups of building characteristics that influence residential energy consumption: (1) factors related to energy efficiency of the building (e.g., construction quality, insulation, energy

efficiency systems, construction materials, etc.); and (2) physical attributes of the building such as housing type and size. This literature review focuses particularly on the effects that a building's physical attributes have on energy consumption.

Housing Size

Housing size has a major positive effect on energy consumption (Kelly 2011; Brounen, Kok, and Quigley 2012; Ewing and Rong 2008; Kaza 2010; Shimoda et al. 2007). According to Ewing and Rong (2008), a 1,000-square-foot increase in housing size will increase energy consumption for space cooling and heating by 13% and 16% (Ewing and Rong 2008, 20).

Number of Rooms

Energy consumption increases as the number of rooms increase (Guerra Santin, Itard, and Visscher 2009).

Housing Type

Residential energy consumption varies across different housing types (Brounen, Kok, and Quigley 2012). This difference is often more significant between single-family and multifamily residential buildings (Kaza 2010). Detached dwellings consume significantly more energy (Brounen, Kok, and Quigley 2012; Guerra Santin, Itard, and Visscher 2009; Ewing and Rong 2008; Baxter et al. 1986; Holden and Norland 2005; Santamouris et al. 2007). This is because a detached home has 'more exposed surface area' than an attached or a multi-family housing unit (Ewing and Rong 2008, 8). This trend in the effect of housing type increases by age of housing (the difference between multi-family and detached housing units is lesser in recently-built dwellings) (Holden and Norland 2005).

Housing Age

Housing age is an important determinant of its energy consumption. In general, older homes consume more energy (Guerra Santin, Itard, and Visscher 2009; Brounen, Kok, and

Quigley 2012; Ewing and Rong 2008; Hirst, Goeltz, and Carney 1982; Santamouris et al. 2007). A possible explanation is that older homes were built at the time of cheaper energy, when there was less concern about energy consumption (Costa and Kahn 2011). The influence of age of building is primarily on space heating (Kaza 2010; Hirst, Goeltz, and Carney 1982).

Tenure Type

The impact of tenure type on residential energy consumption has been less often evaluated, and therefore remains obscure. Yet the literature seems to present more arguments in favor of home ownership rather than renting, in terms of energy consumption trends. Baxter et al. (1986), showed that owner-occupied home are more efficient, compared with rented properties (Baxter et al. 1986). Home owners tend to react to increases in energy cost by increasing investments in energy conservation technologies and efficient appliances (Long 1993). Privately-rented dwelling units consume more energy than privately-owned ones, and when heating is included in the monthly rent, renters consume even more energy (Guerra Santin, Itard, and Visscher 2009).

Housing Choice, Consumption, and Residential Mobility Behaviors

Residential mobility is the main possibility to reestablish equilibrium between households' actual consumption of housing-related services and their needs and desires (Rossi 1955; Quigley and Weinberg 1977; Chevan 1971; Mulder 1996). Since the mid-20th century, different groups of researchers have approached the question 'why do people move?' differently (Simmons 1968). Two distinct strands on mobility motivations are explicit in the literature of residential mobility: 1) mobility in response to locational stress or dissatisfaction, and 2) mobility to maximize utility (W. A. V. Clark, Deurloo, and Dieleman 2006).

Mobility in response to locational stress or dissatisfaction

Rossi (1955) first connected residential mobility behaviors to household satisfaction of their location of residence. Residential mobility, in this context, is an adjustment to endogenous or exogenous changes in households' housing consumption in order to align with the households' needs (Rossi 1955). His initial conceptualization eventually generated theories of residential mobility as a response to environmental or locational stress (Alden Speare 1974; Alden; Speare and Goldscheider 1987; Deane 1990; W. A. V. Clark and Cadwallader 1973).

Locational stressors can be generated either by exogenous circumstances such as changes in residential environment, by endogenous changes such as changes in households' needs (Quigley and Weinberg 1977), or by a combination of both. Speare (1974) posited the 'stress-threshold theory' as a theoretical framework for understanding residential relocation in response to locational stress. According to Speare's theory, households have a threshold level of dissatisfaction that controls their residential mobility behaviors (Alden Speare 1974). Therefore, perception of locational stressors may vary across households (Brown and Moore 1970), and their impacts may diminish over time (W. A. V. Clark and Onaka 1983b).

Dissatisfaction is another key trigger of residential mobility behavior because it directly controls mobility thoughts (Landale and Guest 1985). When dissatisfaction with the location of residence exceeds a tolerable threshold, households will develop the aspiration to relocate (Alden Speare 1974). Households simultaneously evaluate the level of satisfaction from their actual housing by comparing the characteristics of their current dwelling with an alternative location with respect to the future and current needs of the family (W. A. V. Clark and Onaka 1983b). Such multidimensional uncertainties make it difficult to define a reliable measure for satisfaction as the motivation for mobility.

Mobility to maximize locational utility

From an economist's perspective, a commonly implicit assumption in understanding residential mobility behavior is the 'rational decision' of the 'economic actors' toward utility maximization (Simon 1959; Landale and Guest 1985). Households, in this conception, move if their expected gain of utility in an alternative location outweighs the costs of moving (Quigley and Weinberg 1977). Mobility, therefore, is a way of restoring equilibrium between housing demand and the actual housing consumption (Mulder 1996; Boehm and Ihlanfeldt 1986). Therefore, on a supply-demand diagram, the dynamics of mobility reflect as shifts across the demand curve for housing services due to changes in the relative price of housing compared to other services (Hanushek and Quigley 1978).

Although utility maximization may not hold true in many cases of residential mobility, it allows for the operationalization of monetary units as a measure for the motivation of mobility. Yet in reality, households also have passions, needs, and desires, and therefore satisfaction seems to be more relevant than utility maximization in a household's location choice (Alonso 1974).

Complexities Surrounding Mobility Motivation

Although this area of social science is well-established, due to the complexity of the phenomenon the process of residential mobility is not yet fully understood (Kley 2011). The dispersion in research focus, methodology, and outcome has led to a limited understanding of the overall picture, and interactions between various influential factors in the mobility process remain elusive.

Mobility research outcomes are mostly based upon standard quantitative methodologies, which are often limited in capturing the complexities of household mobility behaviors and experiences. Therefore, a main deficiency stems from the oversimplification of the complexities involved in the mobility process to meet the requirements of standard statistical analysis (Winstanley, Thorns, and Perkins 2002). As a result, independent research outcomes have rarely been connected to a broader perspective, which makes it hard to elucidate a comprehensive picture of residential relocation process, its determinants and barriers.

Beyond the debates on whether or not one of the (slightly) different approaches to mobility motivation can provide a better explanation for mobility motivation, the current ‘messiness’ surrounding residential mobility research stems primarily from disciplinary dichotomies (e.g. the dichotomy between sociological and economic approaches). Satisfaction and stress are relatively similar concepts; however, social scientists have often failed to operationalize the idea of mobility in response to locational stress or dissatisfaction by providing robust measurable (or assessable) definitions. One might also consider the economists’ preferred notion on mobility motivation, utility maximization, as a form of obtaining satisfaction. While easier to measure in monetary terms, assumptions based on utility maximization often ignore the non-attitudinal behaviors that can influence individuals to not always make the most preferred choices (Desbarats 1983).

Further, the multidimensionality of the residential relocation process adds to the complexity of the mobility motivation dilemma. On the one hand, households may react differently in response to mobility stimuli, regardless of the type of stimuli. On the other hand, many of the current mobility studies build upon assumptions of free mobility, neglecting possible constraints to household mobility.

Responses to Mobility Stimuli

Although dissatisfaction may decrease by moving to a new residential location, other types of adaptations are also effective in households' response to mobility stimuli (Deane 1990). Other possible responses to mobility stimuli are: 1) modifications in the living environment (Hanushek and Quigley 1978; W. A. V. Clark and Cadwallader 1973), 2) adjustment in expectations (Quigley and Weinberg 1977), or 3) staying neutral³ (Moore and Harris 1979; Brown and Moore 1970; Deane 1990). Nevertheless, a household is not inclined toward moving for the majority of its housing career (Mulder 1996). If residential mobility occurs, regardless of the purpose of the move, a general assumption could be that mobility is an attempt to improve the conditions of residence (Bullamore 1981; W. A. V. Clark 2007; W. A. V. Clark, Deurloo, and Dieleman 2006).

Constraints to Mobility

Residential mobility behavior is highly influenced by various constraints, which may deter or avoid mobility (W. A. V. Clark and Onaka 1983b). The primary constraint toward residential mobility is the cost associated with moving and searching for a new location (Mulder 1996), including energy, time, and money. Such costs are often variable especially depending on the tenure structures. For instance, once a given household becomes a homeowner, its moving costs will significantly grow (Chan 2001). Higher transaction costs of

³ Due to either an inability or an unwillingness to take any of the actions above.

moving is the most commonly cited reason for reduced mobility of homeowners (Dietz and Haurin 2003).

Mobile households may also face social and institutional constraints (Landale and Guest 1985), such as fluctuations in supply and demand in the housing market (Chan 2001). Zoning and other regulatory conditions can also prevent residential mobility by restricting specific groups of households from access to certain locations of residence (Cervero 1996). Such constrained regulatory environments may indirectly hinder residential mobility through increasing costs of moving for all households (i.e. by regulations such as minimum lot size, etc.), or for households of specific racial/ethnic groups (such as social barriers to the mobility of Blacks into mixed-race neighborhoods).

Crowder, South, & Chavez (2006) showed that notwithstanding the racial composition of the origin neighborhood, Blacks are much less likely than Anglos to move to neighborhoods with a predominant Anglo population (Crowder, South, and Chavez 2006). Such differences in mobility rates among racial or ethnic groups suggest that there are other factors related to the social context that create preventive mechanisms in residential mobility (S J South and Crowder 1997; Scott J. South and Crowder 1998b; Alba and Logan 1993; Alba and Logan 1991; Crowder, South, and Chavez 2006; Ioannides and Zabel 2008).

Determinants of Housing Choice, Consumption, and Residential Mobility Behaviors

As discussed earlier, residential relocation is intended to alter the housing consumption in order to either attain satisfaction, eliminate stress, or maximize utility from a specific location of residence. Residential satisfaction develops in an interaction between a household's characteristics and aspirations, the locational attributes of the dwelling unit, and the *social bonds* amongst household members and other people (Alden Speare 1974). Therefore, residential mobility may initiate due to changes in households social and

demographic characteristics or in response to a transformation in factors related to the location of residence (Dieleman 2001b; W. A. V. Clark and Onaka 1983b).

Notwithstanding various classifications of the determinants of intra-metropolitan residential mobility, most influential factors fit into individual and community scales (Oishi 2010). In this categorization, individual factors demonstrate household-related determinants of residential relocation, while community-scale factor encompass contextual determinants. To generate mobility behaviors, factors in both categories directly interact with physical characteristics of the dwelling unit, and indirectly interact with each other.

Household-related determinants of housing choice, consumption, and mobility behaviors

Through multiple interactions, residential mobility behaviors connect with household characteristics (W. A. V. Clark, Deurloo, and Dieleman 2006; W. A. V. Clark and Dieleman 1996). White & Mueser (1988) described residential mobility as a ‘demographic event’ that manifests in geography (White and Mueser 1988). Three major clusters of household-related determinants of housing choice, consumption, and mobility behaviors are: 1) demographic characteristics that are implicit in household lifecycle, 2) economic status, which combines measures of income, occupation, and education, and 3) racial and ethnic status (Simmons 1968). Mobility researchers have often focused on one or only few factors from the three categories of household-related determinants, and the interactions between multiple household-related factors is elusive.

- *Lifecycle/Life Course/Age*

A lifecycle perspective was common in residential mobility studies of the 1950s to 1970s. When people are free to move, residential mobility is the adjustment process through which households match their housing needs at different lifecycle stages with their location of residence (Chevan 1971). While other socioeconomic factors are useful markers in the

mobility process, changes in lifecycle stage are the most significant inducers to mobility of households (Simmons 1968). These changes act as ‘triggers’ generating ‘disequilibrium’ in housing consumption and the subsequent relocation (W. A. V. Clark and Dieleman 1996).

According to the lifecycle approach, households at different lifecycle stages have different housing consumption behaviors (i.e. preferences, needs, requirements), and generally undergo multiple occurrences of transformations in their socioeconomic status. The basic principle is that as households move between lifecycle stages, they re-evaluate the characteristics of either their current neighborhood or current housing unit based on new standards (B. A. Lee, Oropesa, and Kanan 1994). Lifecycle trajectories can cause moves with different distances, directions (e.g. city to suburb), or destinations (e.g. from rented to owner-occupied dwellings) (Mulder 1996).

Residential movements that correspond with lifecycle changes encompass a substantial share of intra-urban moves, independent of housing unit characteristics; however, little evidence exists as to precisely how lifecycle is involved in the decision to move (W. A. V. Clark and Onaka 1983b). This makes it hard to establish a detailed relationship between lifecycle and housing consumption behaviors. In part, this problem is due to vagueness in the definition of lifecycle stages (W. A. V. Clark, Deurloo, and Dieleman 1984; W. A. V. Clark and Onaka 1983b; Quigley and Weinberg 1977).

Much of the classification of lifecycle stages relies on marriage and the presence of children. Abou-Lughod and Foley (1960), for example, described a household’s lifecycle and its associated mobility behavior in 4 stages, including: pre-child, childbearing and childrearing, child-launching, and post-child (Abu-Lughod and Foely 1960). Frey (1978) and Speare (1970) also classified family status in 5 subgroups corresponding to family lifecycle attributes such as marital status, age and presence of children (Frey 1978; Alden Speare 1970).

Although age and lifecycle seem to share similar characteristics and have been used interchangeably (W. A. V. Clark and Dieleman 1996), lifecycle experiences may vary for cohort households (Alden Speare 1970), and thus have different impacts on mobility behaviors. In general, householder age is negatively associated with the probability of moving (Boehm and Ihlanfeld 1986; Landale and Guest 1985; B. A. Lee, Oropesa, and Kanan 1994). However, the possibility of moving in later lifecycle stages never reaches zero (Chevan 1971). Such an inverse relationship between the age factor and mobility is the most consistent similarity among several studies (Quigley and Weinberg 1977). Simmons (1968), in a synthesis of mobility literature concluded that of all moves within a lifecycle stage, about 20% occur for ages under 10, almost 60% happen between the ages of 10 and 40, and 20% after the age of 40 (Simmons 1968).

However, over the course of the past few decades, lifecycle theories of housing behavior have been criticized and gradually substituted by the 'life course' approach, a more flexible and robust approach (van Ham 2012; W. A. V. Clark and Dieleman 1996; Kulu and Milewski 2007; Geist and Mcmanus 2008). The so-called 'oversimplistic' lifecycle theory is generally critiqued for being 'normative' and 'deterministic' and providing analysis categories that are 'politically problematic' (van Ham 2012; Bailey 2008; W. A. V. Clark and Davies Withers 2007). Changes in modern family structures are one of the main reasons for which a natural linear progression of a normative traditional household, as emphasized in lifecycle theories, seems invalid (W. A. V. Clark and Dieleman 1996; Geist and Mcmanus 2008; van Ham 2012).

As an interdisciplinary approach (Bailey 2008; Dykstra and van Wissen 1999), the life course approach connects housing needs and preferences, embedded in interdependent and parallel life events, with housing career (van Ham 2012; Kulu and Milewski 2007). The life course approach envisions household career as a sequence of parallel and interrelated

transitions of life events (e.g., marriage, having children, work and education, etc.) that influence housing choice and mobility decisions (W. A. V. Clark and Dieleman 1996; van Ham 2012; W. A. V. Clark and Davies Withers 2007).

Life course trajectories are linked with housing needs and household preferences, such as space needs, dwelling characteristics, or residential location and amenities (Mudler and Hooimeijer 1999). In the life course approach, age is not the single proxy for life events, and social context plays an important role (Geist and Mcmanus 2008). Life events can happen at any age and still have similar impacts on housing choice and mobility behaviors; therefore, “age is important, but is no longer the defining characteristic of the changes that occur” (W. A. V. Clark and Davies Withers 2007).

Even though lifecycle critics tend to reject the prominence of age in predicting housing career, age is still a primary proxy for life events in many life course-based studies (*see* W. A. V. Clark & Huang, 2003; W. A. V. Clark, 2013; Geist & Mcmanus, 2008). Estimating mobility and housing consumption behaviors based on age (as a single predictor) will most certainly result in big confidence intervals. However, the life course approach poses increased complexities for empirical modeling:

“Life as an evolving process represents interesting perspectives, with excellent prospects for theorizing, but translation into empirical research and statistical analysis represents a major hurdle.” (Willekens 1999, 48)

- *Household Size & Composition*

The mobility debate has established a critical role for the interaction between household size and residential ‘space that the household consumes’ (Beguin 1982; Boehm 1982; W. A. V. Clark, Deurloo, and Dieleman 1984; Chevan 1971; W. A. V. Clark and Huang 2003).

“Housing consumption refers to housing [choice] behavior driven by housing needs and preferences over and above the basic need for shelter.” (van Ham 2012, 50)

The basic premise is that residential mobility is highly influenced by demand for increased space. Changes in family composition (e.g. the presence of children) often imply new space requirements and desires, and thus influence mobility behaviors (W. A. V. Clark and Dieleman 1996; Chevan 1971; W. A. V. Clark and Huang 2003). A larger family size increases the probability of choosing a large unit (Boehm 1982; Ewing and Rong 2008; W. A. V. Clark, Deurloo, and Dieleman 1984). For example, for households who live in crowded housing units, the addition of children triggers mobility (de Groot et al. 2011; W. A. V. Clark and Huang 2003). Therefore, high rates of migration are expected to be associated with areas characterized by small dwellings and a high percentage of adults (Beguin 1982), and/or around the time of a child's birth (W. A. V. Clark, Deurloo, and Dieleman 2002).

- *Income*

Changes in income level can be characterized as an individual-level inducement for residential relocation. The association between income and residential mobility has been discussed by several researchers (Boehm and Ihlanfeld 1986; Boehm 1982; Chan 2001; W. A. V. Clark 2007; Graves and Regulska 1982; Scott J. South and Crowder 1998b), and remains of high importance, especially with regard to housing supply and demand. While the supply of housing is inelastic in the short-run, the demand is defined by the level of local amenities a neighborhood has to offer and a given household's purchasing power, which is directly associated with income level (Chan 2001).

An increase in income can have varying effects on mobility, depending on tenure type and household characteristics (Boehm 1982; Boehm and Ihlanfeld 1986). The association between income and mobility seems to be consistent with households in racial and ethnic groups. Among those who experience residential mobility, higher income increases the probability of moving to a White-dominated area (Scott J. South and Crowder 1998b; W. A. V. Clark 2007).

- *Race or Ethnicity*

Racial mobility rates vary depending on age, tenure type, marital status, and lifecycle stage (Scott J. South and Crowder 1998b). Despite such variations, there is little evidence in prior research to differentiate residential mobility rates for Blacks and Whites. Notwithstanding the racial composition in the origin neighborhood, it has been witnessed that Blacks are much less likely than Anglos to move to neighborhoods with a predominant Anglo population (Crowder, South, and Chavez 2006).

Many of the mobility determinants operate similarly for minority and majority groups. There is relatively slight difference in the socioeconomic statuses of movers and stayers for both Blacks and Whites; however, the magnitude of the influence of each determinant of mobility varies within racial groups (Scott J South and Deane 1993). Attention to locational characteristics is another factor that varies in minority groups compared with majority groups. For example, among locational amenities, various weather variables matter less in non-White migrants compared to White migrants (Graves and Linneman 1979).

A partial explanation for dissimilarities in residential mobility and housing consumption behavior between households of different racial or ethnic groups appears to be provided by the place stratification hypothesis. Minority groups are less likely to become owners on any socioeconomic level (Rossi and Weber 1996). It also has been demonstrated that mobility in Black owners is more frequent than in White owners (Boehm and Ihlanfeld 1986). Furthermore, other findings have shown that between central-city residents, Blacks are more likely to change their location within central cities (S J South and Crowder 1997) and among similar socioeconomic groups. Due to the relatively high constraints to moving, Blacks are significantly less likely to move than non-Blacks (Scott J South and Deane 1993).

Despite the differences in mobility behaviors between minority and majority groups, the impact of individual-level determinants of mobility also vary for individuals of different socioeconomic groups and lifecycle stages within a specific racial or ethnic group. Crowder et al. (2006) showed that for a given African American renter, household size and parental wealth is positively associated with racial assimilation (migration into Anglo-dominated neighborhoods). In contrast, African American homeowners show a much weaker association between wealth and mobility into White neighborhoods (Crowder, South, and Chavez 2006).

Contextual Determinants of Residential Mobility

In the housing choice process, households consider two types of attributes for a bundle of housing services: characteristics related to the dwelling unit (Building-related characteristics), and locational characteristics such as amenities, accessibility, and the socioeconomic status of residents (Dieleman 2001b).

Building-related Characteristics

Much of the housing choice, consumption, and mobility determinants are dwelling unit characteristics pertinent to size, type, and age of the housing unit that directly interact with household characteristics. Therefore, I incorporate the review of prior research on housing size, type, and age within household characteristics, as discussed earlier. Choice of tenure type and impact of duration of residence on housing consumption and mobility behaviors are discussed as follows.

- *Tenure Type*

Along with lifecycle effects, home tenure status is the one of the few background players in housing consumption and mobility process that has a direct and significant influence on household behaviors (Alden Speare 1974; W. A. V. Clark, Deurloo, and Dieleman 1984; S J South and Crowder 1997). For example, homeownership has been shown to significantly reduce mobility (W. A. V. Clark and Huang 2003; B. A. Lee, Oropesa, and Kanan 1994; Alden;

Speare and Goldscheider 1987). On average, renters are 4 to 5 times more likely than homeowners to move across residential location within metropolitan areas (Alden Speare 1970; Quigley and Weinberg 1977). Higher mobility rates are consequently more likely to occur in markets with a large rental stock (Vlist et al. 2002).

Tenure type also reflects variations in the characteristics of households. Evidence has shown that there are large differences among renters and owners in terms of lifecycle and economic status, where homeownership is significantly correlated to age and socioeconomic status of households (Rossi and Weber 1996). Households that own their home are even less likely to move if they have children and are at older lifecycle stages (B. H. Y. Lee and Waddell 2010). In another combination with other socioeconomic characteristics, for instance, a higher income level increases likelihood of mobility for renters, where the same association is not significant for owners (Boehm and Ihlanfeld 1986).

- *Duration of Residence*

Longtime residence at a location, which directly correlates with a household's socioeconomic characteristics, is expected to reduce the chances of moving (B. A. Lee, Oropesa, and Kanan 1994). The effect of duration of residence, 'inertia', is a more important determinant of residential mobility than job-related causes (Bullamore 1981). The situation in which the probability of an individual's mobility decreases by an increase in the duration of residence at that location is called the 'axiom of the cumulative inertia' (Speare 1970). Conversely, a recent move increases the likelihood of mobility (Cadwallader 1982). To overcome inertia, movers need to have enough stimuli such as increased dissatisfaction from the actual residential location or higher perceived utility at an alternative location (Landale and Guest 1985).

Nonetheless, interlinked unobserved factors may influence both the decision to move and the duration of stay. Many of the exogenous socioeconomic or contextual characteristics that increase mobility rates are motives for a shorter duration of stay. For example, smaller houses increase the propensity of shorter stays (for reasons including upgrading of the dwelling unit), and reductions of commute distance to job location can foster longer stay duration (Eluru et al. 2009).

Locational Characteristics

Locational characteristics can influence households' housing choice and mobility behavior, but not so much as they influence households' housing consumption behaviors. I categorize locational characteristics into locational amenities, neighborhood characteristics, jobs-housing balance, and housing market conditions.

- *Locational amenities*

One fundamental discussion about the impact of contextual characteristics on residential mobility is the concept of 'location-specific' amenities (Graves 1979; Graves and Regulska 1982). In addition to job-related reasons, households also move to match their location-specific demands. That is because locational amenities are generally geographically immobile and non-tradable between areas, and households can obtain them only by relocation (Graves and Linneman 1979). Therefore, a joint bundle of amenities is traded with an explicit market price, comprised from implicit prices for each amenity (Graves and Regulska 1982). For this reason, high-priced houses are more likely to have higher qualities, to be larger, to be in neighborhoods with access to more amenities, and lower negative externalities (Waddell, Berry, and Hoch 1993). Thus, an increase in income could initiate migration from locations offering inferior amenities to superior amenities until the equilibrium is reestablished in the wage-rent compensation (Graves and Regulska 1982).

- *Neighborhood characteristics*

Several studies have attributed varying effects of neighborhoods on housing choice, consumption, and mobility behavior (Durlauf 2004; Deane 1990; Cadwallader 1982; Quigley and Weinberg 1977; Boehm and Ihlanfeld 1986). Neighborhood characteristics (including its physical attributes) can predict between 22% and 39% of variations in mobility decisions (Boehm and Ihlanfeld 1986; Beguin 1982). Social and place-specific interrelationships play an important role in creating a sense of identity for households and individuals (Winstanley, Thorns, and Perkins 2002). Therefore, changing the neighborhood can also be a focal determinant of alterations in social status (W. A. V. Clark, Deurloo, and Dieleman 2006). Nevertheless, a decline in neighborhood qualities is expected to be associated with an increase in the probability of moving and vice versa (Boehm and Ihlanfeld 1986).

However, the relative role of the neighborhood in that process is not fully understood (Ewing and Rong 2008; W. A. V. Clark, Deurloo, and Dieleman 2006). Lee, Oropesa, and Kanan (1994) argued that the effect of locational attributes such as distance to work on residential mobility behaviors are secondary, compared to household- and housing-related inducements (B. A. Lee, Oropesa, and Kanan 1994).

- *Jobs-Housing Balance*

In general, job change can increase the likelihood of mobility (de Groot et al. 2011) as a way to optimize the distance to the job location. Yet, it is still difficult to distinguish the dominant causes of intra-metropolitan residential mobility between job- and housing-related factors (Alden Speare 1970; Bullamore 1981). Waddell et al. (2003), demonstrate that in an empirical context the choice of residential location is a priority to choosing job location (Waddell et al. 2007). Similarly, Cervero and Duncan (2006) argue that reasons other than distance to employment locations are more important determinants of residential location patterns (Cervero and Duncan 2006). In general, it appears that sociologists often assume work-

related reasons to be a minor stimulus for residential mobility, while economists believe in a much stronger association (Quigley and Weinberg 1977).

Determining whether jobs follow people or people follow jobs still remains difficult. However, the evidence to date suggests that the former may be more the case than the latter (Nechyba and Walsh 2004). Recalling the concept of place utility, a job may reduce place utility through a reduction in income or occupational status, or both (Bullamore 1981). Proximity to jobs may also influence mobility behaviors through duration of residence. Eluru et al. (2009) demonstrate that reducing the commute distance to job location to under 10km fosters a longer stay duration (Eluru et al. 2009).

At the regional scale, however, commute time remains to be a prevailing element of residential location choice (Levine 1998; Kley 2011). Many studies still struggle with adequately isolating intra-metropolitan residential mobility from inter-metropolitan mobility (i.e. migration). Data from the Current Population Survey (CPS) (King et al. 2010) show that between 1999 and 2010, on average, 47.27% and 36.15% of the overall and intra-state residential mobility in the U.S. happened due to housing-related reasons such as changes in housing tenure, housing price, better neighborhood, and newer and better housing. However, job-related reasons (including new job, job transfer, to look for work, for easier commute to work, job loss, or retirement) were the dominant reasons for residential mobility between the U.S. states, with an average of 41.62% from total mobility reasons (Table 1).

	All Mobility	Intra-State	Inter-State
Household-related reasons	27.20	28.31	26.9
Job-related reasons	18.04	25.71	41.62
Housing-related reasons	47.27	36.15	19.28
Other reasons	7.48	9.83	12.2

Table 1. Average percentages for aggregated categories of mobility reasons in the US between 1999 and 2010 – Data source: Current Population Survey (CPS)

- *Housing Market*

At a larger scale, characteristics of metropolitan areas are also important in defining household demand for housing (Ioannides and Zabel 2008), and therefore in mobility behaviors. Yet very few residential mobility studies have taken the characteristics of metropolitan areas into account (Scott J South and Deane 1993). Factors that influence housing prices also regulate housing stock and migration (Graves and Regulskka 1982; Dieleman, Clark, and Deurloo 2000; Vlist et al. 2002). Mobility also has impacts on the local housing market. Residential relocation generates the turnover of old housing stock (i.e. vacancy and reoccupation of old dwellings) (Strassmann 2001).

Rates of residential mobility vary substantially among different housing markets. Housing markets with a relatively younger population and higher proportion of rental dwellings in the stock are more likely to have higher mobility rates (Dieleman, Clark, and Deurloo 2000). Variation in mobility rates for different housing markets can be explained by the extent of urbanization, the tenure structure, the level of government intervention, and the size of housing market (Vlist et al. 2002).

CHAPTER THREE

Introduction

I discussed in the introduction how current debates on residential energy consumption have been overly focused on the physical characteristics of the housing stock and other technical factors, underestimating the role of the resident household's behaviors. In addition, the standard traditional research has commonly used linear methodologies to analyze energy use in the residential sector, failing to distinguish between direct and indirect effects of the household and the building on energy consumption indices. I developed a conceptual model (Figure 4) based on the hypothesis that the household's effect on energy consumption is twofold: 1) a direct effect, which represents energy consumption behaviors, and 2) an indirect effect through the choice of housing unit characteristics, which I call the housing choice effect. This chapter reviews research data, variables of interest, data preparation steps, and the modeling utilized to operationalize the conceptual model, and measure household and housing effects on energy consumption indices.

Data

I used public microdata from the 13th Residential Energy Consumption Survey (RECS). RECS is a periodic multistage survey sponsored by the U.S. Energy Information Administration (EIA), which provides detailed information on energy consumption in U.S. homes (U.S. Energy Information Administration 2013e). The EIA administers RECS to a nationally representative sample of housing units occupied as a primary residence. Information collected through the survey's three stages (including Household, Rental Agent, and Energy Supplier surveys) has undergone a series of rigorous statistical processes to ensure the highest possible data quality (see Appendix 1 for more information). The EIA asserts that RECS is "the only survey that provides reliable, accurate and precise trend comparisons of energy consumption between households, housing types, and areas of the country." (U.S. Energy Information Administration 2011)

Sampling Strategy

Data for RECS 2009 were collected from 12,083 households (out of a pool of 18,856 households), selected at random using a complex multistage, area-probability sample design. Respondents resided across 3898 segments (census blocks) and 430 primary sampling units (counties). All housing units occupied as primary residences in the 50 States and the District of Columbia, excluding secondary homes, vacant units, military barracks, and common areas in apartment buildings, were eligible to be included in the RECS sample. The sampling was conducted in 3 random selection stages (Figure 11):

- 1- Selection of counties;
- 2- Selection of a sample of segments from the selected counties;
- 3- Selection of housing units from a list constructed from the selected area segments. (Within each selected segment, a list of housing units was created by field listing of residential addresses from the U.S. Postal Service.)

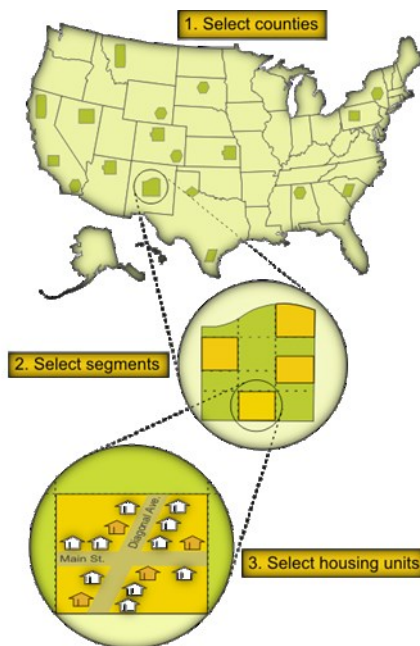


Figure 11. Sampling design of RECS. Source: U.S. Energy Information Administration 2011

Imputations

The EIA applied imputations on missing values (i.e. survey responses such as “Don’t Know” and “Refuse”). For each variable with missing values, the EIA applied a statistical model that determined

a set of “related” variables, from which “statistically similar cases” “donated” their values to the corresponding case (U.S. Energy Information Administration 2013). Imputed responses are identified with ‘imputation flags’ in the public use microdata file. Overall, 9.8% of the variables have at least 1 imputation flag. “EIA recommends using the imputed data, where available to avoid biased estimation.” (U.S. Energy Information Administration 2013f, 6)

Variables of Interest

To investigate the research question, I selected a set of variables representing the household and housing unit characteristics as predictors, in addition to the energy consumption index as the outcome variable. Selected variables that represent the household or the housing unit include characteristics pertinent to the choice of housing unit and energy consumption, as recommended in prior research. I am interested in two energy consumption indices as the outcome variable of two comparable models, the total and the per-capita energy consumption indices. Table 2 illustrates the list of variables of interest:

Variable Category	Variables of Interest
Household Characteristics	Age of Householder
	Gender of Householder
	Racial and Ethnic Status of the Householder
	Household Size
	Household Composition
	Marital Status
	Education
	Employment
	Income
Housing Unit Characteristics	Housing Size
	Number of Rooms
	Housing Type
	Tenure Type
	Housing Age
	Duration of Residence
Energy Consumption Index	Total and per-capita annual energy consumption

Table 2. List of the Variables of Interest

To prepare data for modeling, I conducted listwise deletions and created new variables from other variables. A list of the data preparation steps are provided in Appendix 2.

Modeling

I used Structural Equation Modeling (SEM) to estimate the effect/interralation coefficients of my conceptual model. Originating in the field of biology in the early 20th century, over the past decades SEM has gained popularity with behavioral scientists (Hox and Bechger 2007; Matsueda 2012a) and across many disciplines (Lei and Wu 2007). SEM is a natural progression from factor analysis and (ANOVA)/regression (Iacobucci 2010; Byrne 1998; Lei and Wu 2007), which allows for measuring complex relationships between a set of independent and dependent variables (Hoyle 2012) .

This modeling approach “takes a confirmatory approach to the multivariate analysis of a structural theory bearing on some [theoretical] phenomenon” (Byrne 1998, 3). The structural equation model implies a covariance structure between the observed variable⁴ (Hox and Bechger 2007), representing a series of structural equations (Byrne 1998), to evaluate the validity of a substantive theory with empirical evidence/data (Lei and Wu 2007).

Why SEM?

“Causality” has been a general assumption on estimations from structural equation modeling. SEM methodology can be defined as:

“... a causal-inference engine that takes qualitative causal assumptions, data and queries as inputs and produces quantitative causal claims, conditional on the input assumptions, together with data-fitness ratings to well-defined statistical tests.” (Pearl 2012, 88)

However, there is an important difference that must be taken into account between causation and causal inferences based on sample data. Causal interpretations of structural equation models have created an open area of debate/criticism on the use of SEM.

“Some researchers would naturally prefer a methodology in which claims are less sensitive to judgmental assumptions; unfortunately, no such methodology exists.” (Pearl 2012, 88)

⁴ Synonyms for SEM are covariance structure analysis, covariance structure modeling, and analysis of covariance structures (Kline 2010; Hox and Bechger 2007).

Nonetheless, there are certain benefits and flexibilities associated with the use of SEM methodologies that have increased their popularity, especially in behavioral sciences. SEM, in contrast to the older generation of multivariate procedures, provides the following benefits:

- 1) In addition to observed variables, it can be used to study the relationships between latent constructs that have multiple observed indicators (Lei and Wu 2007; Byrne 1998);
- 2) It takes a confirmatory, rather than an exploratory, approach to data analysis⁵ (Byrne 1998);
- 3) It enables us to model the interactions between model variables, whereas in a regression model the independent variables can have multicollinearity (Dion 2008);
- 4) In contrast to traditional multivariate methods, SEM provides explicit estimates of measurement errors (Byrne 1998).

Estimation Method

Given the popularity of SEM in the behavioral sciences, it is important to recognize the assumptions of different estimation methods, and the corresponding procedures that have to be employed, if such assumptions are not met (Finney and DiStefano 2006). Multivariate normally-distributed continuous variable is the standard assumption for the maximum likelihood estimator (which is the estimator used in most SEM models), likelihood-ratio test statistic, and asymptotic standard errors (Skrondal and Rabe-Hesketh 2005). Violating this assumption can produce biased results (including model fit, parameter estimates, and significance tests), which can in turn result in incorrect deductions about the theory being tested (Finney and DiStefano 2006). However, response variables in behavioral sciences are often noncontinuous. Unlike with multinormally distributed variables, with noncontinuous variables, we cannot base the maximum likelihood estimator on sufficient statistics (e.g. the empirical covariance matrix) (Skrondal and Rabe-Hesketh 2005).

⁵ SEM requires a priori-specified pattern for inter-relationships between variables, lending itself well to inferential analysis of data. Most of the traditional multivariate procedures are, by nature, descriptive, in which hypothesis testing is difficult (Byrne 1998).

One method to address problems encountered when modeling non-normal and/or categorical data involves employing robust WLS estimation methods (Finney and DiStefano 2006; Skrondal and Rabe-Hesketh 2005). Browne (1984) developed the Asymptotically Distribution-Free (ADF) estimator that is thought to be able to accommodate non-normally distributed and/or ordered categorical data (Finney and DiStefano 2006). In LISREL, specifically, this estimator is called weighted least squares (WLS) or ADF (Matsueda 2012b). The WLS estimation procedure “provides optimal estimates for models with non-normal observed variables or ordinal or truncated variables”. (Matsueda 2012b)

Two restrictions limit the practical use of WLS:

- For large models, it requires a much larger sample size (Matsueda 2012b; Finney and DiStefano 2006). The PRELIS program needs $N \geq 1.5k(k+1)$, where K is the number of observed variables.
- It also requires large amounts of computer memory for large models (Matsueda 2012b; Finney and DiStefano 2006).⁶

For data with ordered polytomous variables and mixtures of ordered polytomous and continuous variables, tetrachoric, polychoric and polyserial correlations can be produced (Muthen 1983). In the WLS method, we use polychoric and polyserial correlations in addition to the asymptotic covariance matrix to estimate model parameters.

The Software: LISREL and PRELIS

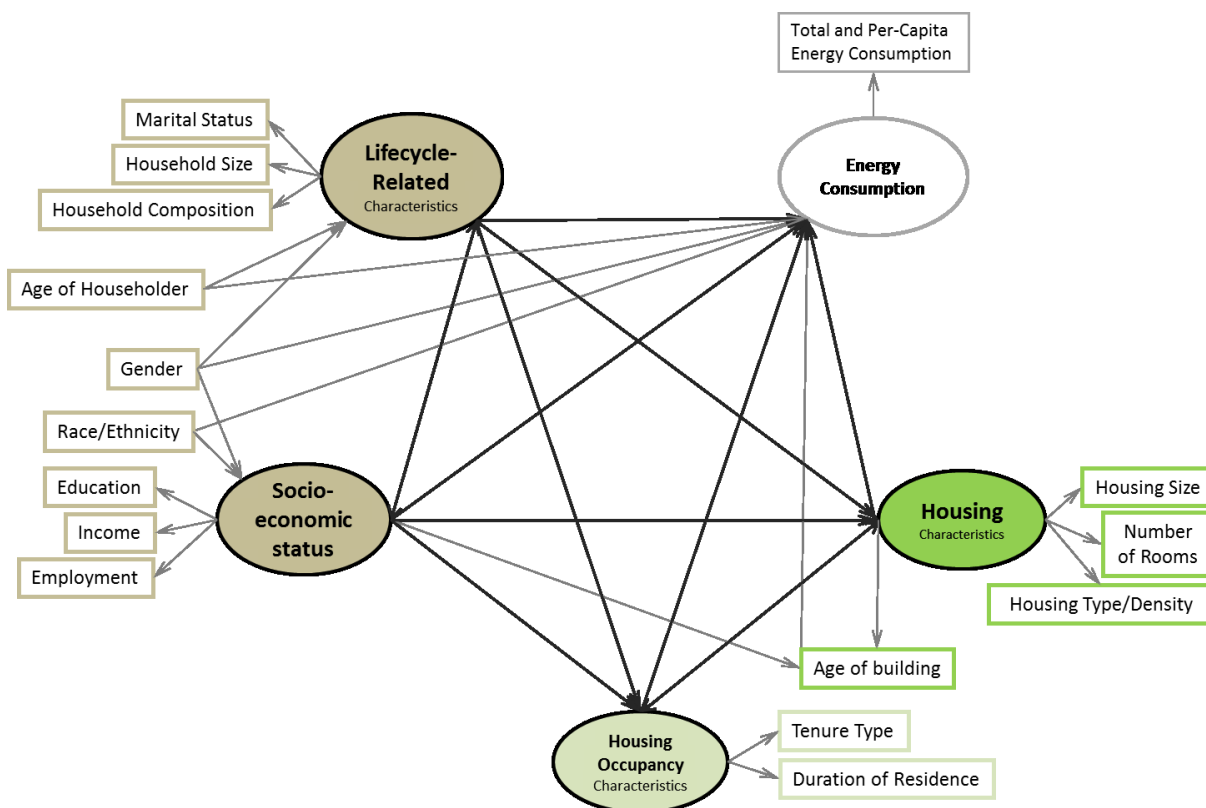
I estimated my model parameters using LISREL (Linear Structural Relations), version 8.8 (Jöreskog and Sörbom 2006a). Due to the existence of categorical and dichotomous data, this program produces Weighted Least Squares (WLS) estimates using an asymptotic covariance matrix, and ‘polyserial’ and ‘polychoric’ correlations provided by the PRELIS 2.8 (Jöreskog and Sörbom 2006b). PRELIS provides ‘polyserial’ correlations between continuous and categorical/dichotomous data, and

⁶ None of these limitations are problematic in this study.

‘polychoric’ correlations between categorical/dichotomous data. The correlation matrix is provided in Appendix 3.

Model Variables and Latent Constructs

Figure 12 illustrates the substantive model, which is designed to operationalize the conceptual model of this study. The substantive model encompasses four latent constructs, four observed predictors (three of which are exogenous), and an observed dependent variable (for the list and description of variables see Appendix 4).



* For easier interpretation of results, I have modeled the observed variables Gender, Race/Ethnicity, Age of Building, and Energy Consumption index in the form of single-indicator latent constructs in which the error variance for the observed variables are constrained to zero.

Figure 12. The Conceptual Model

Besides the dependent variable, which is an index for annual energy consumption, I characterized the predictor [latent constructs and observed] variables according to three categories:

- i. Social and Economic Indicators;

- ii. Characteristics of the Housing Unit; and
- iii. Household's Lifecycle Characteristics.

i. Social and Economic Indicators

I conceptualized social and economic indicators' with one latent construct measuring socioeconomic status (SES), and two exogenous observed variables, indicating race and ethnicity (MAJORITY), and gender (GENDER) (Figure 13). I measured the SES latent construct with the highest education level of the householder, household's annual income, and whether or not the householder is employed. I have set each of these predictors free to have direct effect on the energy consumption index. Moreover, MAJORITY and GENDER can directly influence SES.

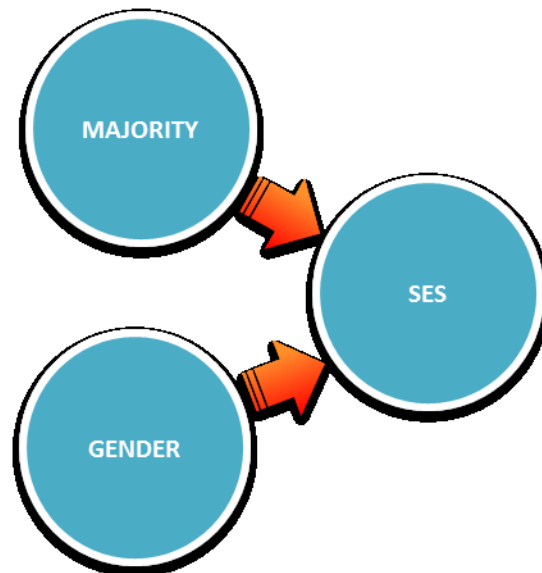


Figure 13. Interactions between Social and Economic Indicators

I hypothesize that being from the Majority group directly influences the energy consumption index, as well as SES, BLD, and RES. The underlying assumption is that membership in the Majority group can have an influence on educational and employment opportunities, and hence on income. In addition, such a social status can directly (and indirectly, through SES) impact housing choices and mobility rates.

In my hypothesis, gender directly affects a household's lifecycle characteristics and SES. I have accounted for the direct effect of gender on the household's lifecycle-related characteristics and SES. Similar to race/ethnicity (MAJORITY), my hypothesis is that GENDER can influence educational and employment opportunities, and hence affect household income. Moreover, the householder's gender can influence the size and composition of the household. Both through SES and household characteristics, I hypothesize that gender can indirectly affect housing choice.

Measurement model specifications for SES

For SES, education is the reference variable. The measurement model (Figure 14) resulted in all significant factor loadings, and Squared Multiple Correlations of 0.29, 0.66, and 0.24 for education, income, and employment indicators.

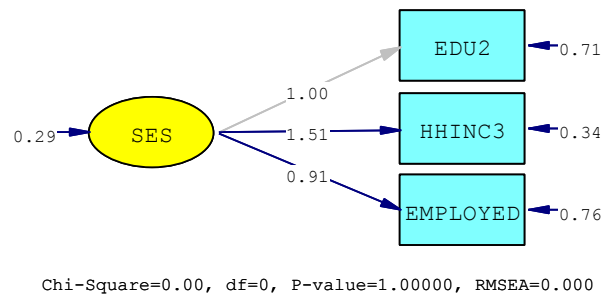


Figure 14. Measurement model for SES

ii. Housing Unit Characteristics

The set of variables that represent housing unit characteristics in this study include two latent constructs and one binary variable. The first latent construct, BLD, provides a measure of housing size, number of rooms, housing type, and tenure type. RES is the second latent construct, representing residency status with two indicators of tenure type (tenure type is a joint indicator here), and a binary variable representing whether or not the household has been residing at the residential location for more than 4 years. In addition to the two latent constructs, housing unit characteristics also encompass a binary variable determining whether the housing unit was built on or after 2000,

representing the newness of construction. According to the conceptual model, building characteristics interact with each other and have direct effects on the total energy consumption index (Figure 15).

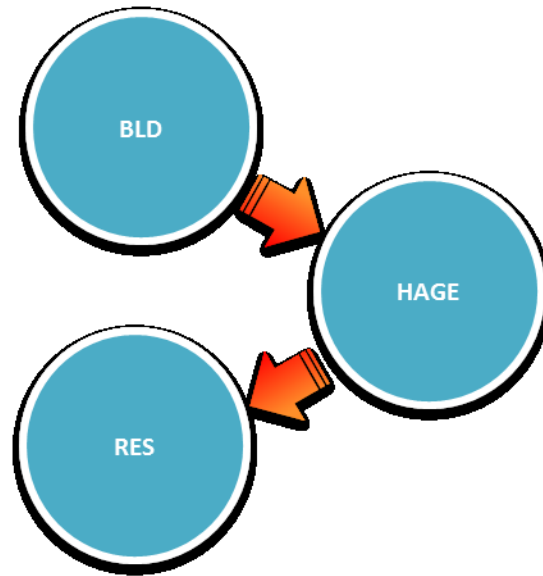


Figure 15. Interactions between Housing Unit Characteristics

I accounted for a direct impact from BLD on HAGE. The underlying rationale for such a direct effect of building characteristics on the age of housing unit is that as building size increases, demolition costs rise, and thus multi-family housing units, for example, can have a higher average age. Additionally, I account for the direct effect of housing unit age on residency status. My hypothesis is that households are more likely to reside for longer in and become the owner of newer housing units, rather than older ones.

Measurement model specifications for BLD

The measurement model (Figure 16) shows that all factor loadings are significant at $p < 0.0001$, verifying the construct validity of the latent constructs. With Squared Multiple Correlations for housing size, type, number of rooms, and tenure type indicators are 0.55, 0.92, 0.63, 0.79.

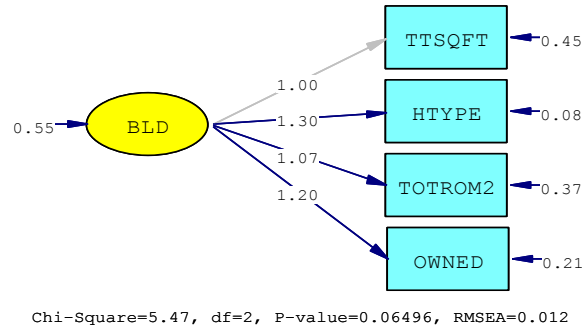


Figure 16. Measurement model for BLD

iii. Household’s Lifecycle-related Characteristics

I created a latent construct that provides a measure for lifecycle-related characteristics of households (HHL D). I defined HHL D with three indicators representing household size (HHSIZE), household composition as measured by the number of adults living in the household (ADULTS), and marital/cohabitation status (SPOUSE). All these indicators are influential in defining a household’s housing needs, and therefore, influential in housing consumption behaviors. In my conceptual model, HHL D has a direct effect on the energy consumption index and housing unit characteristics, is under direct effect of householder age and gender, and correlates with SES (Figure 17).

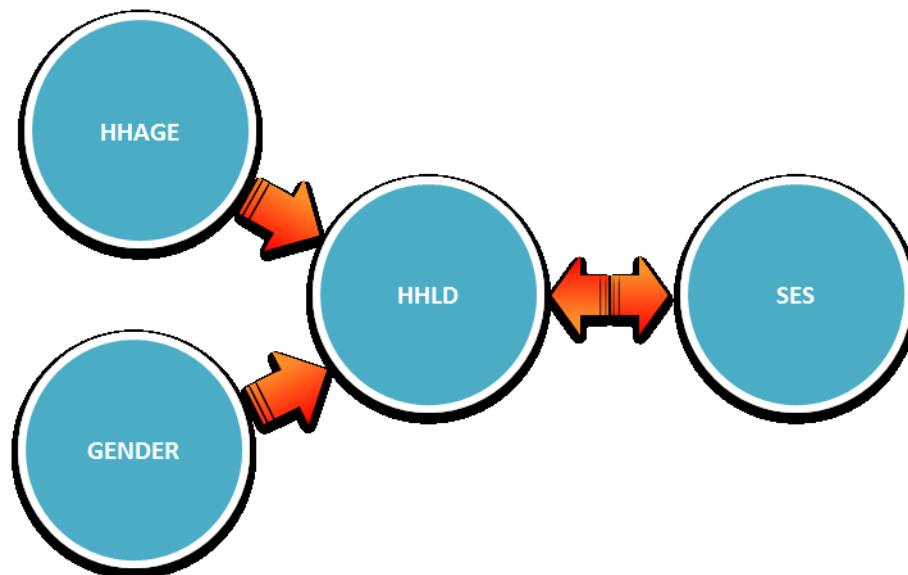


Figure 17. Interactions between Household’s Lifecycle-related Characteristics and Age, Gender, and SES

Measurement model specifications for HHL D

Household size is the reference indicator for the latent construct. The measurement model (Figure 18) resulted in all significant factor loadings ($p < 0.0001$), and Squared Multiple Correlations of 0.72, 0.80, and 0.58 for household size, number of adults, and marital status indicators.

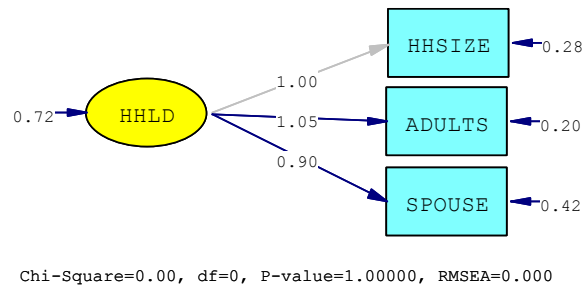
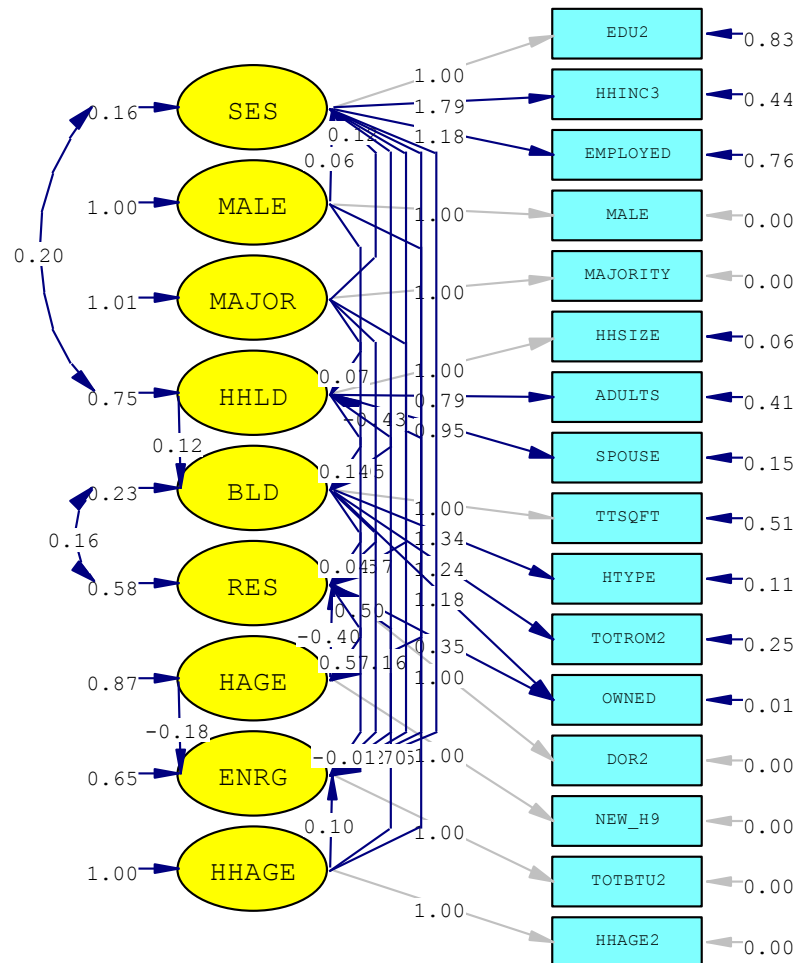


Figure 18. Measurement Model for HHL D

Model Selection

I started modeling by trying to build the substantive model I depicted earlier as the conceptual model with total energy consumption as the outcome variable (Figure 19). However, fit indices (Table 3) do not suggest an acceptable fit for the full conceptual model. Investigating possible causes for the mismatch, I concluded that dropping the householder age variable from the original substantive model decreases chi-square significantly, and consequently, fits the data with much improved fit indices. Consequently, a decision was made to drop the householder age variable.



Chi-Square=9724.95, df=85, P-value=0.00000, RMSEA=0.099

Figure 19. The Original Substantive Model

Table 3 shows model fit indices for the two final models on total and per-capita energy consumption, the “Total” and the “Per-Capita” models. The two models follow the same structure as described in the conceptual model, except in two cases: the outcome variable, and the indicators for the HHL latent construct. In the first model, the Total Model, the outcome variable is total annual energy consumption; whereas in the second model, the Per-Capita Model, per-capita annual energy consumption is the outcome variable (Figure 20). Since I calculate the per-capita index by dividing total energy consumption on household size, I took household size out of the HHL indicators in the Per-Capita Model.

	df	χ^2	RMSEA*	90% C.I. for RMSEA	NFI**	CFI***	SRMR****	Notes
Original Substantive Model	84	9724.95	0.099	(0.097 ; 0.10)	0.9	0.9	0.13	Dropping the HHAGE variable
Total Model	73	4664.5	0.074	(0.072 ; 0.075)	0.94	0.94	0.093	Model on Total Energy Consumption
Per-Capita Model	60	3612.02	0.071	(0.071 ; 0.073)	0.95	0.95	0.081	Model on Per-Capita Energy Consumption

* Root Mean Square Error of Approximation. RMSE smaller than 0.06 to 0.08 with confidence interval (Schreiber et al. 2006; Hooper, Coughlan, and Mullen 2008) suggest acceptable fit. RMSEA in the two selected models are in acceptable range.

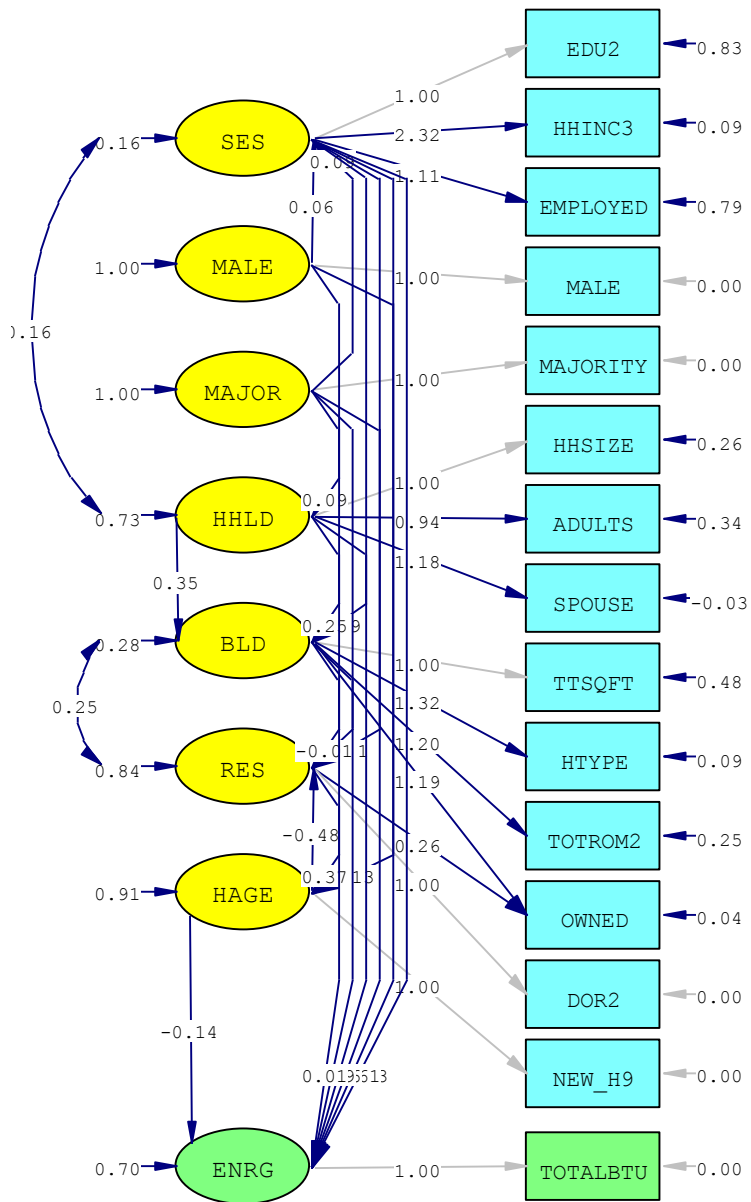
** Normed Fit Index. In an ideal model, NFI is greater than 0.95 (Hu and Bentler 1999).

*** Comparative Fit Index. In an ideal model, CFI is close to 0.95 (or higher) (Iacobucci 2010; Schreiber et al. 2006), or bigger than 0.80 (Hooper, Coughlan, and Mullen 2008) for acceptable fit. CFI index in the two selected models here are close to ideal.

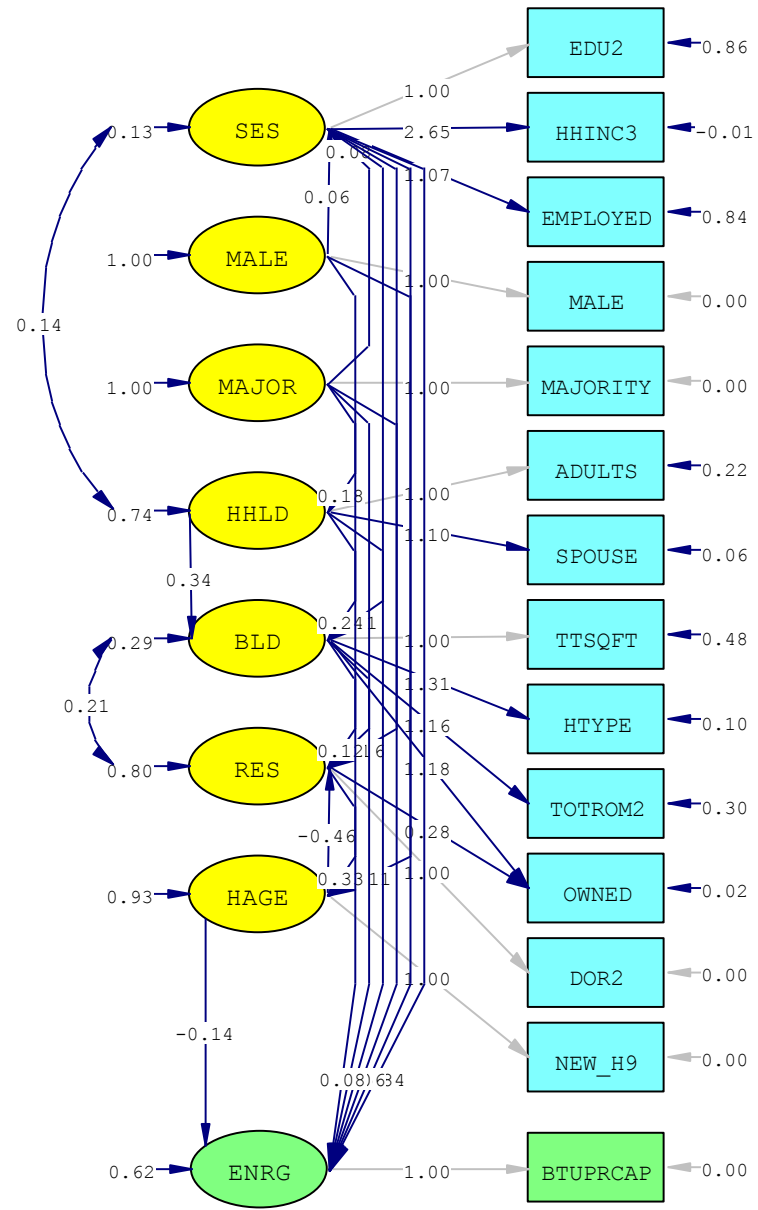
**** Standard Root Mean square Residual. Ideally, SRMR is close to 0.09 (Iacobucci 2010), or bigger than 0.08 (Schreiber et al. 2006). Both selected models in this study have acceptable SRMR indices.

For a brief discussion on fit indices in SEM, see Appendix 5.

Table 3. Model Fit Indices



Chi-Square=4664.05, df=73, P-value=0.00000, RMSEA=0.074



Chi-Square=3612.02, df=60, P-value=0.00000, RMSEA=0.071

Figure 20. The Total and Per-Capita Models

CHAPTER FOUR

Introduction

This section explains the outcomes of the Total and Per-Capita models. Under each model, I provide three tables illustrating the direct, indirect, and total effects. I then explain the modeling results, organized by three categories of variables: Social and Economic Indicators, Household's lifecycle-related Characteristics, and Housing Unit Characteristics. Furthermore, for each of the three main latent constructs (i.e. SES, HHL D, and BLD) in both models, I conduct a sensitivity analysis of the estimates, reported in the Appendix 6.

The Total Model

The Total Model estimates effects on total annual energy consumption, based on the following equations:

$$ENRG = \alpha_1 SES + \alpha_2 MALE + \alpha_3 MAJOR + \alpha_4 HHL D + \alpha_5 BLD + \alpha_6 RES + \alpha_7 HAGE + \epsilon$$

$$SES = \alpha_8 MALE + \alpha_9 MAJOR + \epsilon_{SES}$$

$$HHL D = \alpha_{10} MALE + \epsilon_{HHL D}$$

$$BLD = \alpha_{11} SES + \alpha_{12} MAJOR + \alpha_{13} HHL D + \epsilon_{BLD}$$

$$RES = \alpha_{14} SES + \alpha_{15} MAJOR + \alpha_{16} HHL D + \alpha_{17} HAGE + \epsilon_{RES}$$

$$HAGE = \alpha_{18} SES + \alpha_{19} BLD + \epsilon_{HAGE}$$

where

SES : Socioeconomic Status

MALE: Householder's Gender is Male

MAJOR: Householder is non – Hispanic White

HHL D: Household Characteristics

BLD: Building Characteristics

RES: Duration of Residence

HAGE: Building Age

ENRG: Energy Consumption Index (the outcome variable in each model)⁷

⁷ In the Total Model, ENRG is total annual energy consumption, and the Per-Capita Model represents per-capita energy consumption.

Tables below respectively show the direct (Table 4), indirect (Table 5), and total (Table 6) effects of predictors on total energy consumption.

	SES	MALE	MAJOR	HHL D	BLD	RES	HAGE
SES	--	0.06 <i>(0.00)</i> 16.09	0.09 <i>(0.00)</i> 21.9	--	--	--	--
MALE	--	--	--	--	--	--	--
MAJOR	--	--	--	--	--	--	--
HHL D	--	0.09 <i>(0.01)</i> 9.35	--	--	--	--	--
BLD	0.39 <i>(0.02)</i> 19.79	--	0.25 <i>(0.01)</i> 41.83	0.35 <i>(0.01)</i> 38.92	--	--	--
RES	0.51 <i>(0.03)</i> 18.18	--	0.14 <i>(0.01)</i> 10.19	-0.01 <i>(0.02)</i> -0.48	--	--	-0.48 <i>(0.02)</i> -26.54
HAGE	0.13 <i>(0.02)</i> 6.21	--	--	--	0.37 <i>(0.02)</i> 17	--	--
ENRG	-0.13 <i>(0.04)</i> -3.47	-0.01 <i>(0.01)</i> -1.29	0.06 <i>(0.01)</i> 8.19	0.16 <i>(0.01)</i> 12.58	0.69 <i>(0.02)</i> 32.03	0.01 <i>(0.01)</i> 0.75	-0.14 <i>(0.01)</i> -14.41

Table 4. Weighted Least Square Estimates of the Direct Effects on Total Annual Energy Consumption

Note 1:

In reporting model estimates, two points are standard throughout this chapter:

- 1) All estimates are in standardized units.
- 2) In all tables, standard errors (in parenthesis) and t-values are below the coefficients in Italic.

	SES	MALE	MAJOR	HHL D	BLD	RES	HAGE
SES	--	--	--	--	--	--	--
MALE	--	--	--	--	--	--	--
MAJOR	--	--	--	--	--	--	--
HHL D	--	--	--	--	--	--	--
BLD	--	0.05 <i>(0.00)</i> 13.26	0.03 <i>(0.00)</i> 17.89	--	--	--	--
RES	-0.13 <i>(0.01)</i> -13.2	0.02 <i>(0.00)</i> 9.39	-0.01 <i>(0.00)</i> -2.57	-0.06 <i>(0.01)</i> -12.2	-0.18 <i>(0.01)</i> -12.7	--	--
HAGE	0.14 <i>(0.01)</i> 13.1	0.03 <i>(0.00)</i> 13.52	0.12 <i>(0.01)</i> 21.04	0.13 <i>(0.01)</i> 15.83	--	--	--
ENRG	0.23 <i>(0.01)</i> 15.82	0.04 <i>(0.00)</i> 9.92	0.17 <i>(0.01)</i> 29.98	0.22 <i>(0.01)</i> 25.6	-0.05 <i>(0.01)</i> -10.6	--	0 <i>(0.00)</i> -0.76

Table 5. Weighted Least Square Estimates of the Indirect Effects on Total Annual Energy Consumption

	SES	MALE	MAJOR	HHLD	BLD	RES	HAGE
SES	--	0.06 (0.00) 16.09	0.09 (0.00) 21.9	--	--	--	--
MALE	--	--	--	--	--	--	--
MAJOR	--	--	--	--	--	--	--
HHLD	--	0.09 (0.01) 9.35	--	--	--	--	--
BLD	0.39 (0.02) 19.8	0.05 (0.00) 13.26	0.28 (0.01) 48.47	0.35 (0.01) 38.92	--	--	--
RES	0.38 (0.03) 14.6	0.02 (0.00) 9.39	0.13 (0.01) 10.2	-0.07 (0.02) -4.34	-0.18 (0.01) -12.7	--	-0.48 (0.02) -26.5
HAGE	0.28 (0.02) 14.9	0.03 (0.00) 13.52	0.12 (0.01) 21.04	0.13 (0.01) 15.83	0.37 (0.02) 17	--	--
ENRG	0.1 (0.04) 2.74	0.03 (0.01) 5.06	0.22 (0.01) 37.86	0.38 (0.01) 31.61	0.63 (0.02) 31.86	0.01 (0.01) 0.75	-0.15 (0.01) -21.3

Table 6. Weighted Least Square Estimates of the Total Effects on Total Annual Energy Consumption

Effects of Social and Economic Indicators

According to the substantive model, in addition to the direct effects, social and economic indicators also have indirect effects on the total energy consumption index through their impacts on housing unit characteristics (Figure 21).

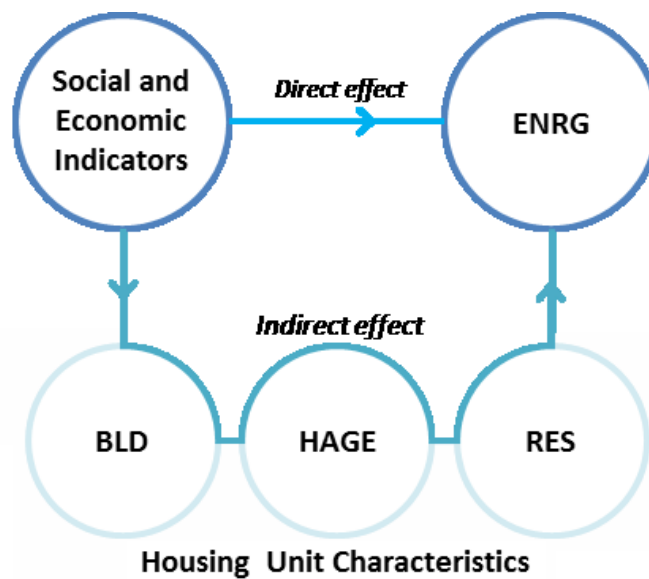


Figure 21. Direct and Indirect Effect of Social and Economic Indicators on Energy Consumption Index

SES

The direct impact of SES latent variable on total energy consumption is -0.13, on standardized units, significant at $p < 0.001$. In other words, a standardized unit increase in SES will decrease total energy consumption by 0.13 of a standardized unit. The indirect impact of SES on energy consumption index is, however, positive (0.23 on standardized units, $p < 0.0001$), leading to a relatively small total effect on energy consumption (0.1, $p < 0.01$). The indirect effect of SES on total energy consumption is through its direct effects on characteristics of the housing unit:

- $IE(SES \rightarrow ENRG) = DE(SES \rightarrow BLD) \times TE(BLD \rightarrow ENRG) + DE(SES \rightarrow HAGE) \times TE(HAGE \rightarrow ENRG) + DE(SES \rightarrow RES) \times TE(RES \rightarrow ENRG)$
- $TE(SES \rightarrow ENRG) = DE(SES \rightarrow ENRG) + IE(SES \rightarrow ENRG)$

Note 2:

IE = Indirect Effect

DE = Direct Effect

TE = Total Effect

(X → Y) = Effect of X on Y

Overall, a standardized unit increase in SES will increase total annual energy consumption by 0.1 of a standardized unit. Since a standard deviation in total energy consumption equals 53,216,734 BTU, a standardized unit increase in SES will directly decrease total energy consumption by 5,321,673.4 BTU. It is important to note that the positive effect on total energy consumption is due to the indirect effects of SES on total energy consumption through its effect on characteristics of the housing unit. The indirect effect of SES on total energy consumption (in absolute value) is larger than its direct effect on energy consumption.

Breaking down the indirect effects of SES on ENRG⁸, the total effect of SES on ENRG is mainly defined by the direct effect of SES on ENRG and its corresponding indirect effect through BLD. Most remarkably, the two effects are contrary to each other. The fact that in the sensitivity analysis SES's effect on total energy consumption is sensitive to the existence of the housing unit parameters provides support for such inverse and complex impacts.

MAJORITY

Being a householder from the Majority group (non-Hispanic and White only) increases a household's total annual energy consumption, compared with householders from a non-White or Hispanic ethnic background. The direct, indirect, and total effects of the variable Majority on the total energy consumption index are, respectively 0.06, 0.17, and 0.22 (all significant at $p < 0.0001$). The direct effect is almost 4 times smaller than the total effect.

If my hypothesis stands, being from a majority group can directly influence the energy consumption index, as well as SES, BLD, and RES. Therefore, the indirect and total effect of MAJORITY on total energy consumption can be calculated as below:

- $IE(MAJORITY \rightarrow ENRG) = DE(MAJORITY \rightarrow SES) \times TE(SES \rightarrow ENRG) + DE(MAJORITY \rightarrow BLD) \times TE(BLD \rightarrow ENRG) + DE(MAJORITY \rightarrow RES) \times TE(RES \rightarrow ENRG)$
- $TE(MAJORITY \rightarrow ENRG) = IE(MAJORITY \rightarrow ENRG) + DE(MAJORITY \rightarrow ENRG)$

Modeling results support my earlier hypotheses that race/ethnicity has direct impacts on socioeconomic status, building characteristics, and residency status. Being from the Majority group increases SES by 0.09 of a standardized unit ($p < 0.0001$) – direct and total effects are

⁸ $DE(SES \rightarrow BLD) \times TE(BLD \rightarrow ENRG) = 0.2457, p < 0.0001$
 $DE(SES \rightarrow HAGE) \times TE(HAGE \rightarrow ENRG) = -0.0195, p < 0.0001$
 $DE(SES \rightarrow RES) \times TE(RES \rightarrow ENRG) = 0.01, non-significant at p < 0.05$

equal here.⁹ In addition, being from the Majority group both directly and indirectly affects characteristics of the housing unit. The direct effect of MAJORITY is 0.25 on BLD and 0.14 on RES, both significant at $p < 0.0001$. Indirectly, through the impact on SES, being from the Majority group only marginally influences RES, BLD, and HAGE – it decreases RES (-0.01, $p < 0.05$), increases both the BLD and the likelihood of living in a newer housing unit by 0.03 of a standardized unit ($p < 0.0001$), and increases by 0.03 ($p < 0.0001$). Overall, being from the Majority group ‘improves’ characteristics of the housing unit. The total effects of MAJORITY on BLD, RES, and HAGE are respectively 0.28, 0.13, and 0.12 (all significant at $p < 0.0001$).¹⁰

Similar to SES, MAJORITY’s indirect effect on total energy consumption is significantly larger than its direct effect. Decomposing the indirect effect of MAJORITY on total energy consumption¹¹ shows that its largest effect (indirect and direct) is through its effect on BLD.

GENDER

In the conceptual model, I have accounted for the direct and indirect effect of gender on energy consumption. Gender’s indirect effect, in my hypothesis, is through its impact on household’s lifecycle-related characteristics and SES, as formulated below:

- $IE(\text{GENDER} \rightarrow \text{ENRG}) = DE(\text{GENDER} \rightarrow \text{SES}) \times TE(\text{SES} \rightarrow \text{ENRG}) + DE(\text{GENDER} \rightarrow \text{HHLD}) \times TE(\text{HHLD} \rightarrow \text{ENRG})$

⁹ This could be interpreted as membership in the Majority group increasing the householder educational attainment by 0.09, annual income by 0.20, and chance of employment by 0.10 ($p < 0.0001$).

¹⁰ That also could be interpreted as membership in the Majority group increasing housing size and total number of rooms by 0.28 and 0.34 of a standardized unit. In such a case, housing type would tend toward single-family housing (from multi-family) by 0.37, the likelihood of ownership (vs. rentership) would increase by 0.37, and the likelihood of residence for more than 4 years would increase by 0.13 of a standardized units. Moreover, the Majority householder is 0.12 of a standardized unit more likely to live in a home, which was built on or after 2000.

¹¹ $DE(\text{MAJORITY} \rightarrow \text{SES}) \times TE(\text{SES} \rightarrow \text{ENRG}) = 0.009$
 $DE(\text{MAJORITY} \rightarrow \text{BLD}) \times TE(\text{BLD} \rightarrow \text{ENRG}) = 0.1575$
 $DE(\text{MAJORITY} \rightarrow \text{RES}) \times TE(\text{RES} \rightarrow \text{ENRG}) = 0.0014$

- $TE(\text{GENDER} \rightarrow \text{ENRG}) = IE(\text{GENDER} \rightarrow \text{ENRG}) + DE(\text{GENDER} \rightarrow \text{ENRG})$

Model results suggest that the householder's gender (being male vs. female) does not have a significant direct impact on total energy consumption (-0.01, insignificant at $p < 0.5$). However, being a male householder increases SES by 0.06, and HHLD by 0.09 of a standardized unit ($p < 0.0001$).¹² Therefore, through the impacts on HHLD and SES, a male householder will increase total annual energy consumption only marginally (0.04, $p < 0.0001$), leading to a total effect of 0.03, significant at $p < 0.0001$.

Furthermore, impacts of gender on SES and HHLD can slightly improve characteristics of the housing unit. Total effects of householder's gender (male householder) on BLD, RES, and HAGE are 0.05, 0.02, and 0.03, respectively – all significant at $p < 0.0001$. These effects, for example, could also be interpreted as if a male-householder household is 0.03 of a standardized unit more likely to reside in a newer home.

Effect of Household's Lifecycle-related Characteristics

According to the conceptual model, the latent construct HHLD can have both direct and indirect impacts on the total energy consumption index. Similar to SES, the indirect impact goes through the effects of HHLD on housing unit characteristics; in particular, on the BLD and RES latent constructs (Figure 22).

¹² Consequently, this can be interpreted as: indicators of SES and HHLD increase if the householder is male. When the householder is male, highest educational attainment and employment chances increase by 0.06 standardized units, and total household income increase by 0.13 of a standard deviation. On a similar assumption, household size and total number of adults increase by 0.09 of a standard deviations, and the householder would be 0.11 of a standard deviation more likely to live with a spouse – all coefficients significant at $p < 0.0001$.

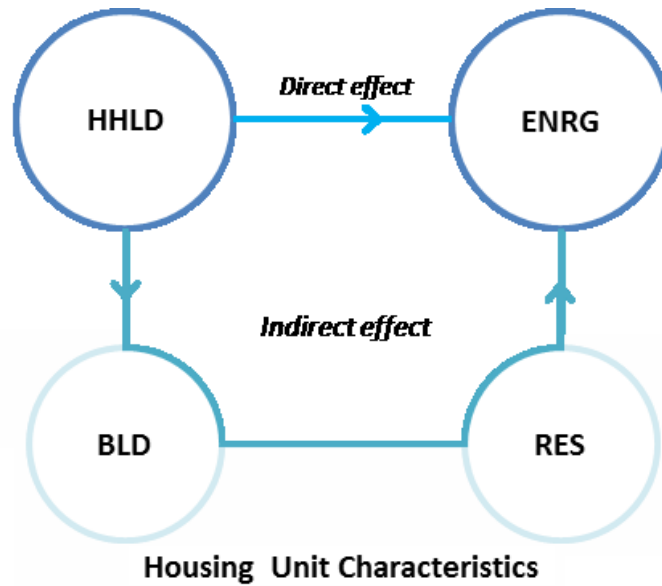


Figure 22. Direct and Indirect Effect of Household's Lifecycle-related Characteristics on Energy Consumption Index

Model results show that HHL's direct impact on total annual energy consumption is 0.16, on standardized units ($p < 0.0001$). In other words, a standardized unit increase in HHL¹³ increases the energy consumption index, directly, by 0.16 of a standardized unit. HHL's indirect effect on total energy consumption, through its impacts on building characteristics and residency status, is larger. A standardized unit increase in HHL will increase total annual energy consumption by 0.22 indirectly, leading to a total effect of 0.38, significant at $p < 0.0001$.

- $IE(HHL \rightarrow ENRG) = DE(HHL \rightarrow BLD) \times TE(BLD \rightarrow ENRG) + DE(HHL \rightarrow RES) \times TE(RES \rightarrow ENRG)$
- $TE(HHL \rightarrow ENRG) = DE(HHL \rightarrow ENRG) + IE(HHL \rightarrow ENRG)$

As discussed above, this model accounts for the direct effect of household's lifecycle-related characteristics on building characteristics (BLD) and residency status. The underlying idea

¹³ This could also be interpreted as increasing household size by 1, number of adults by 0.94, and likelihood of the householder living with a spouse by 1.18 of a standardized unit.

is that as a household grows in size and alters in composition or marital status, needs for housing, and therefore, mobility rates will change. Results provide proof for this assumption. According to the modeling outcomes, a standardized unit increase in HHL D will improve BLD, directly by 0.35 ($p < 0.0001$) – total and direct effects are equal in this case (due to lack of indirect effect). However, the direct effect of HHL D on RES is insignificant at $p < 0.05$.

Through its effect on building characteristics, HHL D has indirect effects on the age of the housing unit and on residency status. The indirect effect of HHL D on whether or not the housing unit was built on or after 2000 (HAGE) is 0.13 ($p < 0.0001$), and on RES is -0.06 ($p < 0.0001$). Overall, a standardized unit increase in HHL D will slightly reduce chances of longer [than 4 years] residence in a residential location (-0.07, $p < 0.0001$), and will increase the likelihood of the household's choice of a newly built housing unit by 0.13 of a standardized unit, significant at $p < 0.0001$ (total and indirect effects on HAGE are equal).¹⁴

Similar to SES, breaking down the indirect effect of HHL D on total energy consumption¹⁵ shows that the largest effect (direct and indirect) of HHL D on total energy consumption is its indirect effect through BLD (0.22, $p < 0.0001$). HHL D's direct effect on total energy consumption is smaller in magnitude than its indirect effect on BLD.

¹⁴ Total effect of HHL D on building characteristics could also be interpreted as that a unit increase in HHL D:

- increases housing size and total number of rooms by 0.35 and 0.42;
- shifts housing type towards single-family housing by 0.46;
- increases the likelihood of ownership by 0.4;
- decreases the likelihood of residency for more than 4 years by 0.07; and
- increases the likelihood of residence in a housing unit for less than 9 years by 0.13.

All coefficients in standardized unit and significant at $p < 0.0001$.

¹⁵ $DE(HHL D \rightarrow BLD) \times TE(BLD \rightarrow ENRG) = 0.2205, p < 0.0001$
 $DE(HHL D \rightarrow RES) \times TE(RES \rightarrow ENRG) = -0.0001, non-significant at p < 0.05$

Effects of Housing Unit Characteristics

Unlike household characteristics that can affect energy consumption both directly and indirectly, in my conceptual model housing unit characteristics only have direct effects on energy consumption indices.¹⁶ Therefore, housing unit characteristics constantly carry the indirect effect of household characteristics within their direct effect on energy consumption indices.

BLD

Modeling results show that BLD's direct effect embraces the largest effect amongst all estimates (direct, indirect, and total) in this study. One standardized unit increase in BLD will increase total annual energy consumption by 0.69 of a standardized unit, significant at $p < 0.0001$. BLD's indirect effect – through its effect on age of the housing unit – is negative, though (-0.05 , $p < 0.0001$), leading to a total effect of 0.63, significant at $p < 0.0001$. In other words, a unit increase in BLD, directly will increase total energy consumption by 33,526,542.42 BTU; the amount of energy needed to cool or heat 33,526,542.42 pounds of water by 1 degree Fahrenheit. (See sensitivity analysis in Appendix.)

- $IE(BLD \rightarrow ENRG) = DE(BLD \rightarrow HAGE) \times TE(HAGE \rightarrow ENRG)$
- $TE(BLD \rightarrow ENRG) = DE(BLD \rightarrow ENRG) + IE(BLD \rightarrow ENRG)$

Model outputs provide evidence for the effect of BLD on HAGE, as I hypothesized in the conceptual model. A standardized unit increase in BLD¹⁷ will increase the likelihood of housing unit being built in the past 9 years by 0.13 of a standardized unit ($p < 0.0001$).

¹⁶ Except for the hypothesized direct effect of BLD on HAGE, which associates with an indirect effect on energy consumption for BLD.

¹⁷ Which could also be interpreted as a unit increase in housing size, 1.2 unit increase in total number of rooms, 1.32 unit increase in tendency of housing type toward single-family housing (from multi-family), and 1.19 unit increase in the likelihood of ownership (vs. renting)—all in standardized units.

RES and HAGE

Effect of the residency status on total energy consumption is close to zero (0.01) and insignificant at $p < 0.05$. Residency status, however, positively “correlates” with BLD (0.25, $p < 0.0001$). Additionally, results indicate the contrary of my hypothesis that HAGE has an effect on RES (i.e. households are more likely to reside longer in and be the owner when the housing unit is newer). A standardized unit increase in the likelihood of the housing unit being newly built will decrease RES by 0.48 standardized units, significant at $p < 0.0001$, meaning that the newer housing units are less likely to be owner-occupied and/or have residents living in them for more than 4 years.¹⁸ This result make sense, to some extent, as housing units that were built in less than 9 years are less likely to have residents living in them for more than 4 years, compared with older buildings.

Not surprisingly, newer homes decrease total energy consumption. A standardized unit increase in the housing age latent construct (HAGE) will directly decrease the energy consumption index by 0.14 standardized units ($p < 0.0001$). The corresponding total effect is only marginally larger (-0.15, $p < 0.0001$). That is, a standardized unit increase in the likelihood of the housing unit being younger than 9 years old will decrease 7982510.1 BTU from the total annual energy consumption at a given housing unit.

¹⁸ This effect could be interpreted as a standardized unit increase in HAGE decreasing the likelihood of home ownership by 0.12 and more than 4-years residence by 0.48 standard deviation, $p < 0.0001$.

The Per-Capita Model

In addition to the household-level outcome variable (the total annual energy consumption index), I also developed a second model with per-capita energy consumption as the outcome variable. Since I calculated the per-capita index by dividing the total index on household size, results of this model represent (semi) individual-level effects on the outcome variable. The two models can be complimentary to each other by providing information on household-and individual-level energy consumption behaviors.

Tables below show model estimates of the direct (Table 7), indirect (Table 8), and total (Table 9) effects of the predictors on per-capita annual energy consumption.

	SES	MALE	MAJOR	HHLD	BLD	RES	HAGE
SES	--	0.06 (0.00) 17.1	0.08 (0.00) 21.28	--	--	--	--
MALE	--	--	--	--	--	--	--
MAJOR	--	--	--	--	--	--	--
HHLD	--	0.18 (0.01) 16.6	--	--	--	--	--
BLD	0.41 (0.02) 18.5	--	0.24 (0.01) 40.64	0.34 (0.01) 31.78	--	--	--
RES	0.46 (0.03) 15.4	--	0.21 (0.01) 14.3	0.12 (0.02) 6.98	--	--	-0.46 (0.02) -26.1
HAGE	0.11 (0.02) 5.01	--	--	--	0.33 (0.02) 15	--	--
ENRG	-0.54 (0.06) -9.7	0.08 (0.01) 11.8	0.08 (0.01) 10.56	-0.56 (0.02) -30.3	0.8 (0.02) 36.2	0.08 (0.01) 7.16	-0.14 (0.01) -15.9

Table 7. Weighted Least Square Estimates of the Direct Effects on Per-Capita Energy Consumption

	SES	MALE	MAJOR	HHL D	BLD	RES	HAGE
SES	--	--	--	--	--	--	--
MALE	--	--	--	--	--	--	--
MAJOR	--	--	--	--	--	--	--
HHL D	--	--	--	--	--	--	--
BLD	--	0.08 (0.00) 19.58	0.03 (0.00) 16.63	--	--	--	--
RES	-0.11 (0.01) -11.8	0.03 (0.00) 12.69	-0.01 (0.00) -2.09	-0.05 (0.00) -11.1	-0.15 (0.01) -11.7	--	--
HAGE	0.13 (0.01) 11.81	0.03 (0.00) 16.45	0.1 (0.01) 18.88	0.11 (0.01) 13.82	--	--	--
ENRG	0.32 (0.02) 17.42	-0.07 (0.00) -16.3	0.18 (0.01) 26.73	0.26 (0.01) 20.98	-0.06 (0.01) -10.4	--	-0.04 (0.00) -7.51

Table 8. Weighted Least Square Estimates of the Indirect Effects on Per-Capita Energy Consumption

	SES	MALE	MAJOR	HHL D	BLD	RES	HAGE
SES	--	0.06 (0.00) 17.1	0.08 (0.00) 21.28	--	--	--	--
MALE	--	--	--	--	--	--	--
MAJOR	--	--	--	--	--	--	--
HHL D	--	0.18 (0.01) 16.6	--	--	--	--	--
BLD	0.41 (0.02) 18.5	0.08 (0.00) 19.6	0.28 (0.01) 48.38	0.34 (0.01) 31.78	--	--	--
RES	0.34 (0.03) 12.3	0.03 (0.00) 12.7	0.2 (0.01) 14.87	0.07 (0.02) 4.23	-0.15 (0.01) -11.7	--	-0.46 (0.02) -26.1
HAGE	0.25 (0.02) 12.9	0.03 (0.00) 16.5	0.1 (0.01) 18.88	0.11 (0.01) 13.82	0.33 (0.02) 15.01	--	--
ENRG	-0.22 (0.05) -4.41	0.01 (0.01) 2.29	0.26 (0.01) 46.48	-0.3 (0.01) -21.5	0.74 (0.02) 35.64	0.08 (0.01) 7.16	-0.18 (0.01) -27.3

Table 9. Weighted Least Square Estimates of the Total Effects on Per-Capita Energy Consumption

Effects of Social and Economic Indicators

SES

The direct impact of SES latent variable on per-capita energy consumption is -0.54, significant at $p < 0.001$. Similar to its effect on total energy consumption, the indirect impact of SES on the energy consumption index is positive (0.32 on standardized units, $p < 0.0001$). However, the large negative direct effect coefficient shifts the total effect of SES on per-capita

energy consumption to the reverse direction (-0.22, $p < 0.0001$), compared with the total consumption index. Overall, one standardized unit increase in SES will decrease per-capita annual energy consumption by 0.22 of a standardized unit.

MAJORITY

The direct, indirect, and total effects of MAJORITY on energy consumption index are, respectively 0.08, 0.18, and 0.26, all significant at $p < 0.0001$. That is, a householder from the Majority group will increase per-capita annual energy consumption in that household, compared with the householder being from a non-Majority group. In other words, household members whose householder is from a Majority group, consume more energy individually (or on average), as compared with members of other households.

GENDER

Unlike the total consumption model, results on the per-capita energy consumption suggest that the householder being male (vs. female) has a statistically significant and positive direct impact on per-capita energy consumption (0.08, significant at $p < 0.0001$). Household members whose householder is male tend to increase the average individual-level energy consumption. However, through its impacts on HHL and SES, a male householder will, indirectly, decrease per-capita energy consumption at the household by 0.07, significant at $p < 0.0001$ – both HHL and SES have negative total effects on per-capita energy consumption. Due to the contrasting direct and indirect effects, the total effect of householder gender on per-capita energy consumption is only marginal (0.01, significant at $p < 0.05$).

Effect of Household's Lifecycle-related Characteristics (HHL)

Outcomes suggest that an increase in HHL will directly decrease per-capita annual energy consumption by 0.56, on standardized units ($p < 0.0001$). However, the corresponding indirect

effect, through its impacts on building characteristics and residency status, is positive (0.26, $p < 0.0001$), leading to a total effect of -0.30, significant at $p < 0.0001$.

Impact of the Housing Unit Characteristics

BLD

Directly, a standardized unit increase in BLD will increase per-capita annual energy consumption by 0.8 of a standardized unit, with a corresponding indirect effect equal to -0.06 ($p < 0.0001$). As such, the total effect of BLD on per-capita energy consumption is 0.74, significant at $p < 0.0001$.

RES and HAGE

One standardized unit increase in RES will increase per-capita energy consumption (directly and totally) by 0.08, significant at $p < 0.0001$. Similar to the total model, newer homes decrease the per-capita energy consumption index. A standardized unit increase in the housing age variable (HAGE) decreases per-capita energy consumption by 0.14 directly, and 0.18 of a standardized unit in total ($p < 0.0001$).

CHAPTER FIVE

Introduction

This chapter offers a summary of the modeling results, a discussion of this research's contributions, concluding remarks on this study's policy implications, and a summary in intended future work deriving from this research.

Summary of Findings

For the first time since the energy crisis of the 70s, this time due to its considerable impact on climate change, residential energy consumption is becoming a 'hot' area of energy policy debate. Yet, compared with other sectors that consume energy, the residential sector has lingered behind in research and policy attention (Kelly 2011; Aune 2007; Lutzenhiser 1992; Moezzi and Lutzenhiser 2010; Ewing and Rong 2008). Due to key methodological and theoretical deficiencies (reviewed in chapter two), conventional wisdom on household energy consumption is filled with uncertainties (if not fallacies) (Lutzenhiser et al. 2010). Energy consumption and GHG emissions levels are likely to increase in the coming decades (U.S. Energy Information Administration 2013a), underlining the fact that our policies and plans haven't been successful enough (Drummond 2010; Boswell, Greve, and Seale 2010).

Building upon initial research findings by Ewing & Rong (2008), Kelly (2011), and Steemers & Yun (2009), this research developed a conceptual model that accounts for both direct and indirect effects of household characteristics on energy consumption. The indirect effect of household characteristics on energy use is through their effect on the housing unit: the housing choice effect. According to this conceptual model, once a household chooses a certain housing unit, there will be a permanent effect of that choice on the household energy use at that particular housing unit.

Research Contributions

The first goal of this research was to improve the current state of knowledge by a) isolating the direct, indirect, and total effects on energy use, and b) examining role of additional household- and housing-related variables on residential energy consumption. This research incorporated variables that have not been included in residential energy research before, such as householders' gender, marital status, number of adults, and duration of residence, and added further insight on the effect of known variables. In addition, this study introduced latent constructs that quantitatively represent abstract social and physical phenomena (e.g., SES), and can be used to elevate conventional wisdom on determinants of residential energy consumption.

Below is a short summary of this research's findings on the two energy consumption indices, categorized by latent constructs:

Socioeconomic Status (SES). SES directly decreases both energy consumption indices. Indirectly, however, through its effect on the housing unit characteristics, SES increases both indices of household energy use. The indirect effect of SES on total energy consumption, in absolute value, is larger than its direct effect. Overall, a standardized unit increase in SES will increase total energy consumption by 0.1 standardized unit. In other words, households from higher socioeconomic groups (e.g., with higher income and education) consume more energy annually only because they are living in more energy-consumptive housing units (e.g., bigger single-family homes, with more rooms), not because they have more energy-consumptive behaviors.

Majority. The direct effect of the householder being from the Majority group is positive on both energy consumption indices, yet small. Majority's larger effect on both outcome variables is indirect, through its effect on building characteristic. Overall, a householder from the

Majority group increases total (by 0.22) and per-capita (by 0.26) energy consumption indices. In other words, if a given householder is non-Hispanic White, that household's energy consumption is higher mainly because they live in more energy-consumptive homes. So, if minorities consume less energy, it is mainly because they often tend to reside in less energy-consumptive buildings.

Gender. Gender of the householder does not have a significant direct effect on total energy consumption, but will slightly increase the per-capita index. Overall, both effects are statistically significant, yet marginal in magnitude.

Household's Lifecycle-related Characteristics (HHLD). As household's lifecycle-related characteristics increase, total energy index increases (by 0.16). The indirect effects of HHLD on both energy consumption indices are positive. Overall, an increase in household's lifecycle-related characteristics will increase total energy consumption. In other words, as households move through their lifespan (e.g., become larger, more adults in household, etc.), their total annual energy consumption increases because they have more energy users, and also because they tend to choose larger quantities of housing as their need for residential space (e.g., more rooms, more square footage, etc.) grows.

Building Characteristics (BLD). Building characteristics' effects on energy consumption are the largest, compared with the effect of all other influential factors accounted for in this modeling. Overall, when residential buildings are larger, with more rooms, and are single-family, both energy consumption indices increase, quite considerably.

Age of the Housing unit (HAGE). Not surprisingly, as housing units become older, energy consumed in those homes increases.

Duration of Residence (RES). Longer residence slightly increases the per-capita energy consumption index. However, its effect is not significant (either magnitude-wise or statistically) on the total index. In other words, this research does not support that ownership and longer duration of residence in residential locations can significantly influence energy use.

Direct vs. Indirect Effects

The primary goal of this research was to isolate direct and indirect effects from the total effect on energy consumption. **Error! Reference source not found.** shows that, aggregating all indirect and direct effects on ‘total’ energy consumption, the cumulative indirect effects are only slightly smaller in magnitude than direct effects, signifying the importance of indirect effects. **Error! Reference source not found.** illustrates that indirect effects on energy consumption constitute the larger share of household characteristics’ effects (first four columns from left); in contrast, many of the effects of housing unit characteristics are direct.

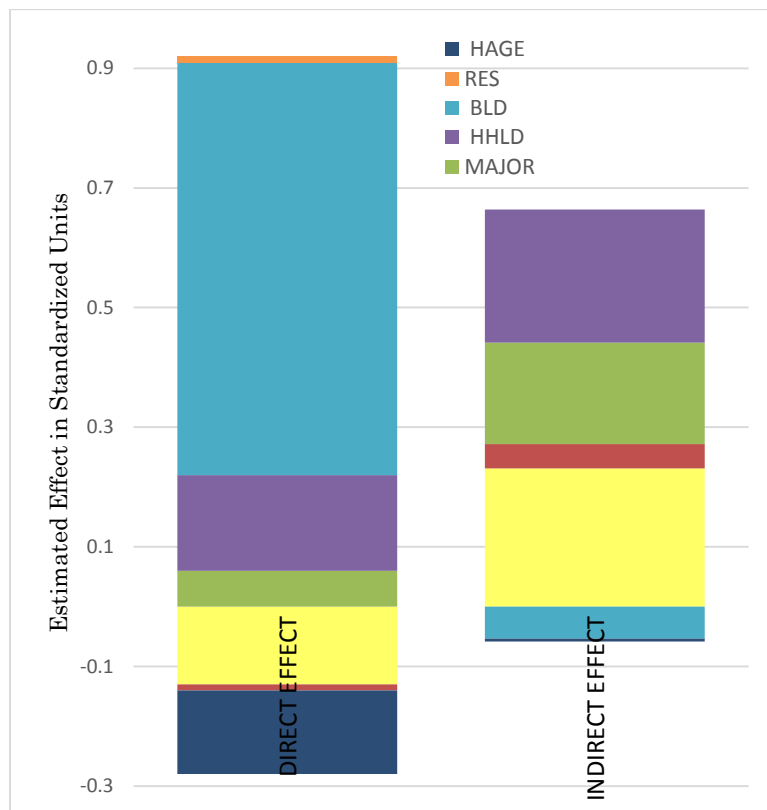


Figure 23. Direct & Indirect Effects by Magnitude

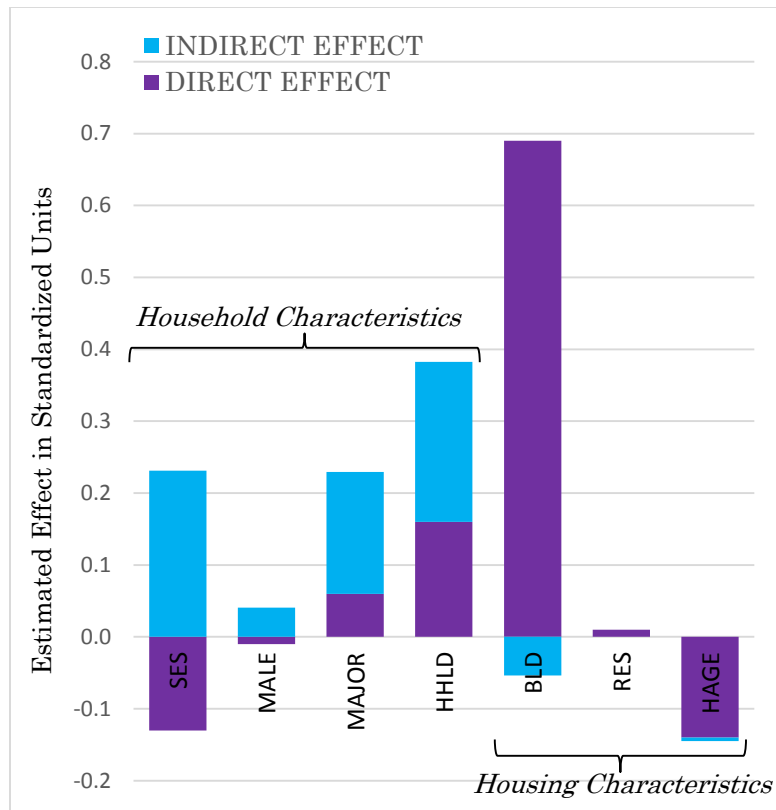


Figure 24. Effects by Type and Magnitude

Indirect Effects

After illustrating the relative importance of indirect effects on the 'total' energy consumption index, the following figures show their sources and mediators. **Error! Reference source not found.** shows that, from all the indirect effects on total energy consumption, the largest portion happen through BLD, building characteristics. In other words, dividing the indirect effects that go through BLD (i.e., indirect effects of SES, HHL D, and MAJOR) by all indirect effects, 86.8% of all indirect effects on total energy consumption operate through the choice of housing unit characteristics such as type, size, and number of rooms. **Error! eference source not found.** shows that SES, HHL D, and MAJOR have the three largest indirect effects, much of which happen through housing unit characteristics.

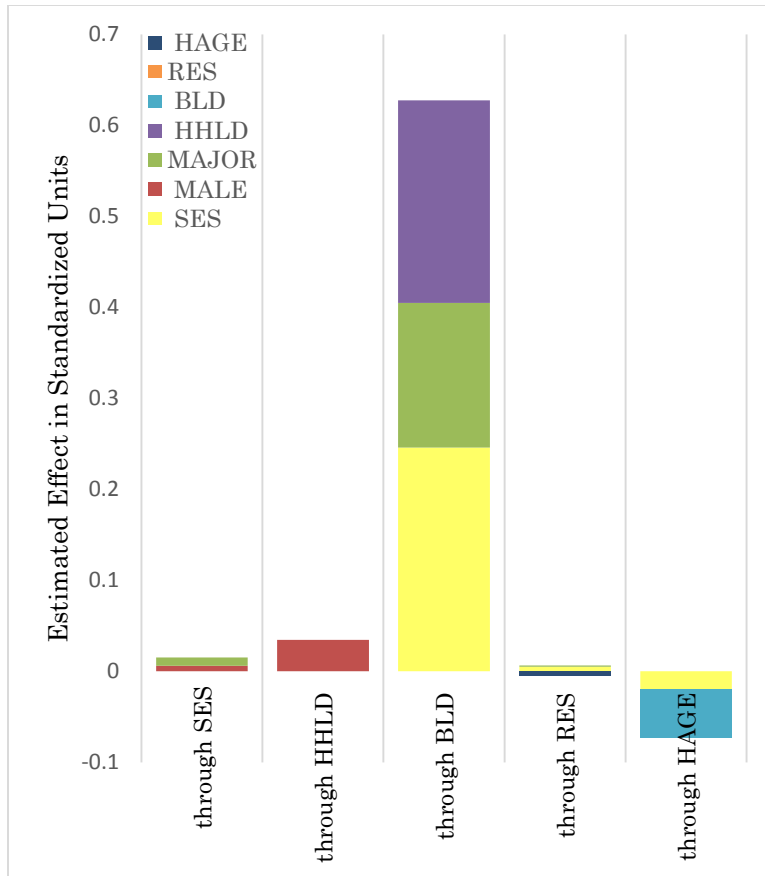


Figure 25. Indirect Effects by Mediator

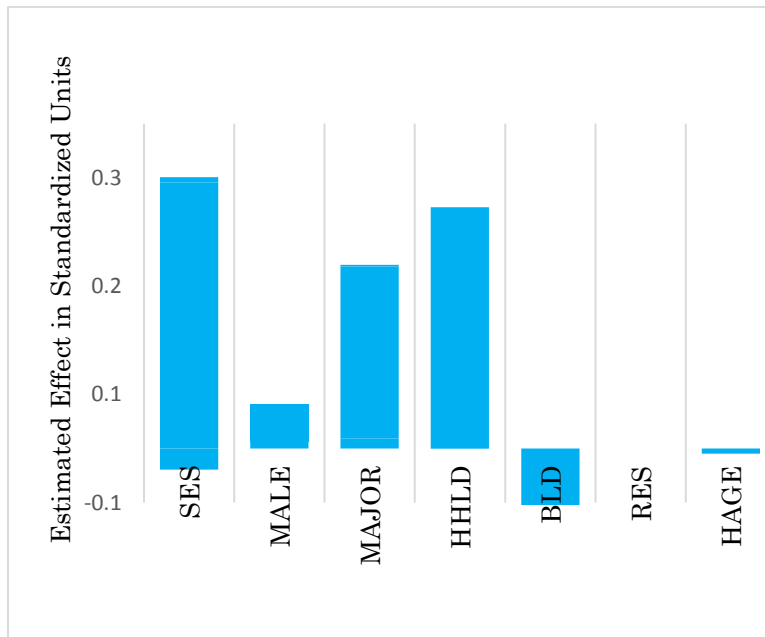


Figure 26. Indirect Effects by Magnitude

Methodological Contribution to Energy Policy

The second goal of this research was to transform urban energy policy and planning by introducing a novel approach to household energy consumption that connects residential energy use to underlying housing choice, consumption, and mobility behaviors. One of the key deficiencies of research on residential energy use is that traditionally used linear methodologies do not account for the complexities involved in household energy consumption. To be able to adequately compare the modeling conducted in this study, I modified the ‘Total Model’ with no mediations between the latent constructs and ran the model as the ‘Linear Model’. So, similar to a linear regression modeling framework, in the Linear Model all latent constructs predict the outcome variable and do not have any effect on another predictor. Model fit indices (Table 10) demonstrate that the covariance structure from the Total Model fits data significantly better than the Linear Model.

MODEL	df	χ^2	χ^2/df	RMSEA	90% C.I. for RMSEA	NFI	CFI	SRMR
Total Model	73	4664.5	63.897	0.074	(0.072 ; 0.075)	0.94	0.94	0.093
Linear Model	87	26011.15	298.97	0.16	(0.16 ; 0.16)	0.68	0.68	0.23

Table 10. Comparing Model Fit Indices between the Total Model and the Linear Model

I used estimated coefficients of the Linear Model to compare the results obtained from two models. Figure 27 illustrates the comparison between estimated effects from the Linear and the total effect estimates from the Total energy consumption models. An interesting pattern is that, similar to standard research findings, the Linear Model overestimates the effect of 2/3 of housing characteristics, and underestimates the effect of 3/4 of household-related characteristics. For example, the Linear Model estimates the effect of building characteristics (BLD) on total energy consumption almost twice bigger/larger than what this research estimated.

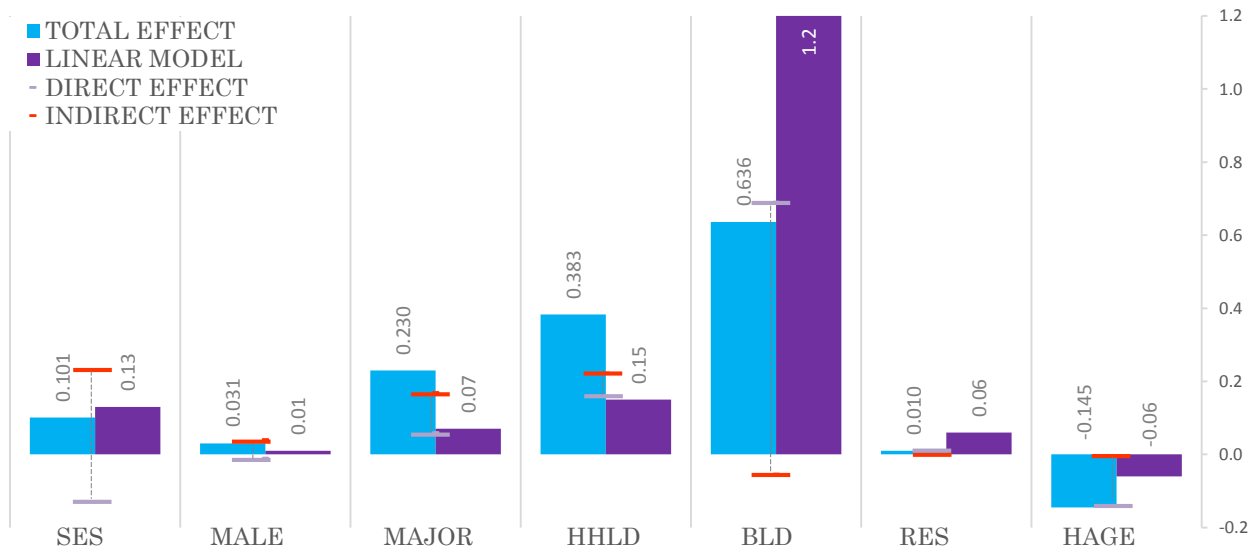


Figure 27. Comparing the Linear and Total Models

In contrast to the overestimation of building effects by the Linear Model, the Total Model (this research) estimates that the effect of household characteristics (HHL D, MAJOR, and MALE) is much larger than the estimates of the Linear Model. This supports the view that traditional methods suffer from a methodological deficiency in underestimating the household's role. Figure 27 also shows the direct and indirect effects estimated by the Total Model. For all three household characteristics underestimated by the linear model, the Linear Model's estimates are missing the indirect effects on total energy consumption. In fact, estimated direct effects are almost equal to the effects estimated by the Linear Model.

Another contribution of this research to energy policy is that distinguishing between direct and indirect effects provides planners and policy-makers with information that is 'actually' useful. As illustrated in Figure 27, there is little difference in the estimates of the two models on the effect of SES on total energy consumption. Both models suggest that an increase in SES will increase total energy consumption, reinforcing prior research findings. However,

such a finding is not useful for policy per se – i.e., it is nonsense to establish policies to slow down economic and educational development to reduce energy consumption.

The estimated direct and indirect effects in this research demonstrate that SES directly reduces energy consumption, and it is its indirect effect that changes the aggregated (total) effect to positive. **Error! Reference source not found.** also showed that SES's main indirect effect on energy consumption is through characteristics of the housing unit. That is, households in higher SES groups (those with higher income, higher education, and who are employed) have more efficient energy consumption behaviors, but this is because they live in homes that are more likely to be bigger, detached, and to have more rooms their aggregated energy consumption increases.

Housing Choice Plays an Important Role in Determining Energy Use

This study's findings can be summarized in a short sentence: housing choice is important! I demonstrated in this dissertation that energy consumption is an outcome (among many) of housing choice, consumption, and mobility behaviors. At the end of the day, even after taking all factors into account, residential energy consumption is the outcome function in which the household and the housing unit play the ultimate role (Figure 28, i). For example, energy price influences the way households behave, and local climate impacts local construction patterns and behaviors. If there were no household in a housing unit, or no housing unit for a given household, notwithstanding the energy price or local climate, no residential energy would be consumed.

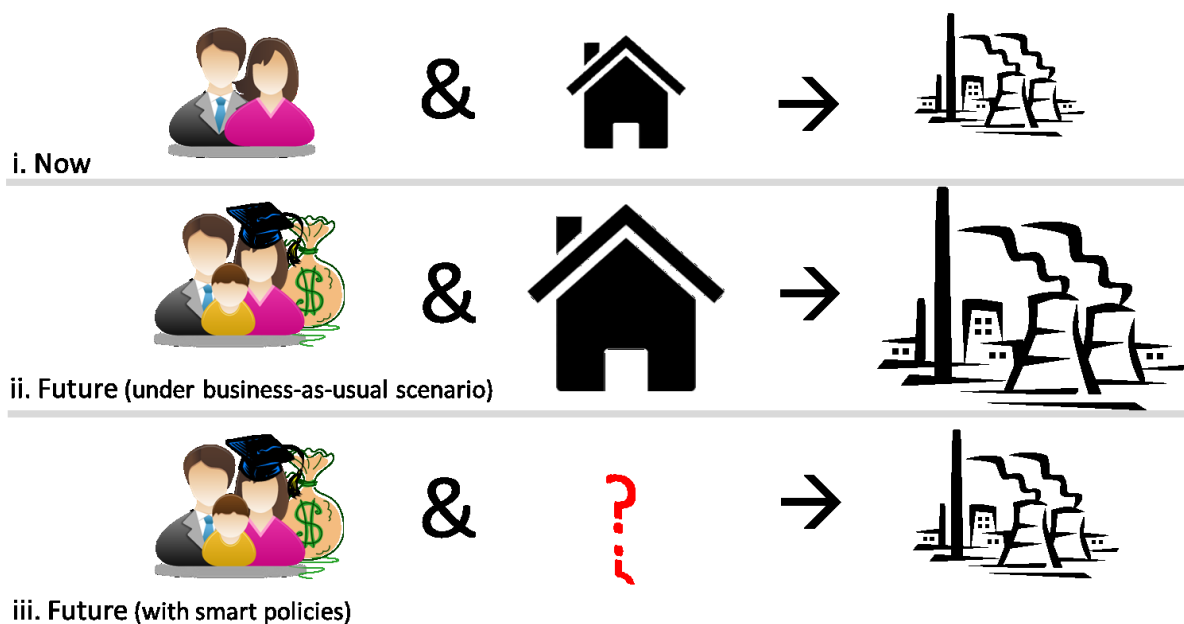


Figure 28. Future policies need to be “smarter” to preserve energy

Socio-demographic and economic characteristics are dynamic, as societies change constantly. Any change in household characteristics is likely to influence housing and choice and consumption behaviors. If the household is able to relocate, under a business-as-usual scenario, an increase in a household’s housing consumption will influence their housing choice, and consequently increase their energy consumption (Figure 28, ii).

Smart energy (and climate change) policies will need the implementation of new and innovative ideas, which are often considered “radical departures from business-as-usual” processes (Wheeler 2008, 489). Innovation in design and construction of future housing is key to reducing environmental and economic costs and to improve quality of life in urban areas. Towards this goal, planners need to stimulate innovative homebuilding practices (Koebel 2008). Not only should smart policies promote energy efficiency in buildings, they should provide more sustainable housing opportunities for households with different socio-demographic and economic characteristics.

What should be the characteristics of such sustainable housing? This is the question with which I conclude this dissertation. Especially as climate change will have repercussions on our communities, future homes should be affordable, and both technologically and architecturally innovative and resilient.

Translating Results into Policy: Future Work

“For the theory-practice iteration to work, the scientist must be, as it were, mentally ambidextrous; fascinated equally on the one hand by possible meanings, theories, and tentative models to be induced from data and the practical reality of the real world, and on the other with the factual implications deducible from tentative theories, models and hypotheses.” (Box 1976, 792)

What differentiates this research from a “pure” social sciences research is its orientation towards policy and planning practice. Despite such practical orientation, however, producing explicit energy policies was not amongst the goals of this study. The second goal of this research was to transform urban energy policy and planning by introducing a novel outlook to residential energy use. This study’s results demonstrate that multiple interactions, mediations, and interdependencies are involved in the process of residential energy consumption. In other words, the process of residential energy consumption is complex. This study also showed that untangling complexities can provide information that are actually “useful” for policy and planning.

The better we – as individuals, planners, policy-makers, etc. – process complexities, the better decisions we’ll make. In the previous section, I concluded that future policies need to be smarter – they should take more complexities into account. Yet there are a couple of additional complexities due to which I chose not to aim at proposing explicit smart policies that might be derived from the outcomes of this study.

First, the level on which the outcomes of this research are generalizable does not perfectly match the level at which policies are often established. The data used in this study represents the US population (i.e., the national level). The policies that planners often have to deal with, however, rarely go beyond the regional level and are mostly focused on the urban and neighborhood levels. Considering the heterogeneity of housing markets, climate, and population characteristics across the US, it is likely that the estimates of this model (and any other statistical model) vary significantly for different localities. Therefore, any local- or regional-level policy recommendation should be based on data from the corresponding geographic scale and adopt modeling specifications that match the characteristics of the respective regulatory environments.

Second, the traditional planning process is not capable of directly incorporating complex scientific outcomes into policy development. The three primary steps in traditional planning process are: (1) gathering data; (2) transforming data into information; and (3) setting goals and objectives. Policies often follow explicit goals arrived at as the fourth step in the traditional planning process. The results of this study showed, for example, that through housing choice race/ethnicity indirectly affects energy use. There seems to be a missing link to go from this finding to producing policy; perhaps an interface that can help planners and policy-makers set explicit goals for their respective communities.

The planning process needs modification to adapt to (and benefit from) a new era, with the abundance of data and growing advances in computer analytics (often talked of as the “Big Data” era). What is required for the outcomes of this study to be used in planning and policy is a paradigm shift in planning practice: a modified planning process (Figure 29).

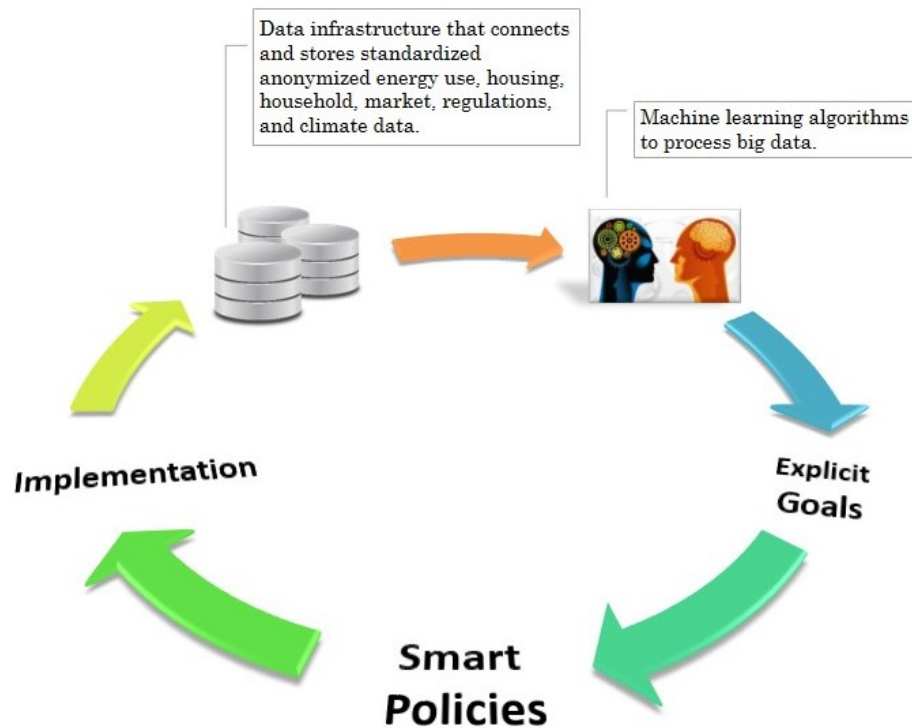


Figure 29. A Modified Planning Process Implementing My Future Work on Energy Policy Tools

As I mentioned earlier, the traditional planning process often begins with data gathering. I also discussed in the introduction and literature review that data unavailability is an important issue that hinders the advancement of residential energy consumption research and policy. Local utility companies are concerned about privacy issues. In addition, energy data needs to be connected to population, market, and climate data in a standardized way, to become useful for research and policy purposes.



The first step in my proposed planning process is a data infrastructure comprised of energy, population, market, regulations, and climate data. There are various examples of such data infrastructures in health sciences that were developed using appropriate data governance methods and information architectures. Given that the bars for privacy are set

much higher for health data than for energy data, it should be feasible to develop similar data infrastructures for energy policy and research.



New technologies (e.g., cloud computing, etc.) have made it easier to share and store data. Computer processing and analytics are also advancing rapidly, making it possible to process more data and complexities, faster and more efficiently (in its statistical denotation). In this research, I used Structural Equation Modeling and included latent constructs in my model to understand some of the complexities in residential energy consumption by testing a hypothetical covariance structure against a national-level dataset. SEM is a confirmatory approach, but there are several other analytical approaches (Machine Learning techniques, in general) that can analyze more complexities, and can provide simulations. I suggest that the traditional analysis in planning process (step 2) should be enhanced/replaced by incorporating advanced Machine Learning algorithms.

The findings of such analyses and simulations need to be made explicit via a policy interface. Using the policy interface, planners and policy-makers would be able: (1) to explicitly monitor the effects of various variables on energy consumption and results of a simulated intervention, and (2) to modify the analytical algorithms, if needed, to improve the outcomes. The interface should provide explicit goals for planners and policy-makers, making it easier to reach conclusions and assumptions. For example, such an interface would show the planner that reducing impact of income on housing size by X% will decrease energy consumption by Y%.

From these explicit goals, designing smart policies is only a function of the planners'/policy-makers' innovativeness in finding the best ways (i.e., smartest policies) for their respective localities to achieve their goals. Though it would have been possible for me to translate the outcomes of this research into goals, the second reason I did not attempt to recommend

policies is that I strongly believe solutions to be context-dependent. For example, if reducing the impact of income on housing size by X% was the goal, then changes in property taxes might be the best option in one region, while in another region changes in design codes could be the solution. Once smart policies are implemented, the results will be captured in the data infrastructure and used for further re-iterations of the proposed planning process.

I empirically verified in this research that housing choice is important in determining residential energy consumption. More importantly, this study introduced a new approach to energy policy research: accounting for more complexities of the energy consumption process can improve conventional understanding and produce results that are useful for policy. More elaboration around the proposed modified planning process will embrace a significant part of my future academic career. As of completing this dissertation, I will be working on developing more complex algorithms to understand more of the complexities in household energy use and housing consumption behaviors, in order to improve energy, housing, and climate change policy.

APPENDICES

Appendix 1: RECS data collection and quality procedures

Data acquisition for the RECS is accomplished through a Household Survey. For each selected housing unit, specially trained interviewers use a standardized questionnaire to collect its energy characteristics, usage patterns, and household demographics. The field interviewer uses a laptop to record the householder's responses to the survey (referred to as the Computer-Assisted Personal Interview method). “Household interviews averaged 51 minutes and were conducted with a household member knowledgeable about energy use in the home. In most cases, this was a householder.” (U.S. Energy Information Administration 2013e) 419 interviewers conducted the data collection in a six-month period, from February to August 2010. Where necessary, bilingual interviewers conducted interviews in Spanish. Information from the household survey is combined with data from energy suppliers to these homes to provide and estimate of energy costs and usage for end uses. (U.S. Energy Information Administration 2011)

To increase accuracy, the EIA uses the Rental Agent Survey, where respondents in rental housing units are less sure of their housing unit’s energy characteristics. This survey is conducted by phone or in person from the unit's landlord or a representative. The data collected through the two surveys (Household and Rental Agent Surveys) undergo through a series of rigorous statistical processes to ensure the highest possible data quality. Upon the completion of the Household and Rental Agent Surveys, the EIA conducts a third round of surveys, the Energy Supplier Survey (ESS), a follow-up mail survey conducted by energy supplier companies who provide services to the selected housing units. The Energy Supplier Survey collects data on consumption of electricity, natural gas, fuel oil, and propane by the sampled households through the reference year. RECS uses this to estimate total energy consumption and expenditure, excluding estimates for energy sources such as biomass (wood) or solar, “for which data are difficult to obtain.” (U.S. Energy Information Administration 2013e)

Appendix 2: Data Preparation

Below is a brief overview of the data preparation steps:

- 1) Deleted records with the following criteria:
 - a) In 1.1% of households (n=137), the household's fuel bills included fuel used for non-household purposes.
 - b) 1.8% (n=221) of the households reported to have "activities that use an unusual amount of energy".
 - c) 1.2% (n=135) of cases resided in housing units with an unknown tenure type ("Occupied without payment of rent").

After deleting all the above-mentioned cases, the total sample size for this study is 11,590.

- 2) Created variables from existing information/other variables:
 - a) To calculate the number of adults in the household, I counted household members above 19 years old as adults.¹⁹
 - b) I created a new variable, in which I calculated per-capita energy consumption by dividing total energy consumption by household size.
 - c) The available 5 categories for the "type of housing" included mobile homes, two types of single-family, and two types of multi-family housing. These categories are only nominal, and cannot be treated as ordinal. I created a new variable, which characterizes housing type based on both the housing unit and the resident household characteristics. In the new variable, I merged mobile homes into the single-family detached category.
 - d) I created a new variable representing the age of housing structure²⁰ by deducting the year in which the housing unit was built from 2009.
 - e) Because most people had moved into their housing units within the 4 years prior to the survey, the original duration of residence variable had a skewed distribution. I created a

¹⁹ The cutoff age of 19 was decided on because I only had age categories for the second to fourteenth household members. The 4th age category for household members in the dataset was 15-19. Only 63 of the householders between 16 and 19 were counted as kids.

²⁰ The EIA made a few modifications on the public microdata to avoid disclosure of personally identifiable information:

- The year of construction for sampled housing units (YEARMAD) was bottom coded at 1920.
- The variable HHAGE (age of the householder) was top-coded at 85.

new binary variable representing whether the household has lived in the housing unit for more than 4 years (collapsed categories for more than 4 years of residence).

- f) The variable total number of rooms had a skewed distribution. I created a new variable in which I collapsed the categories for number of rooms greater than 11.
- g) I created a new binary variable for employment status by counting part-time employed as employed.
- h) I created a new binary variable for Majority that combines race and ethnicity. Non-Hispanic White only householders are marked as Majority.
- i) The original categories for education did not conform to an ordinal scale appropriate for analysis in this study. I created a new categorical variable out of the original categories with more “meaningful” categories for educational attainment.
- j) The household income variable was top-coded and did not have consistent intervals. I created a new categorical variable with consistent \$5,000 intervals.

Appendix 3: The Correlation Matrix

	EDU2	HHINC3	EMPLOYED	MALE	MAJORITY	HHSIZE	ADULTS	SPOUSE	TTSQFT	HTYPE	TOTROM2	OWNED	DOR2	NEW_H9	TOTALBTU	BTUPRCAP
EDU2	1															
HHINC3	0.44	1														
EMPLOYED	0.26	0.4	1													
MALE	0.05	0.16	0.18	1												
MAJORITY	0.2	0.23	-0.08	0.07	1											
HHSIZE	-0.02	0.23	0.21	-0.01	-0.24	1										
ADULTS	-0.02	0.31	0.1	0.12	-0.12	0.76	1									
SPOUSE	0.12	0.47	0.14	0.23	0.08	0.64	0.68	1								
TTSQFT	0.26	0.45	0.06	0.05	0.28	0.21	0.23	0.37	1							
HTYPE	0.06	0.35	0.00	0.07	0.33	0.29	0.34	0.42	0.7	1						
TOTROM2	0.23	0.44	0.09	0.02	0.25	0.34	0.33	0.4	0.72	0.76	1					
OWNED	0.21	0.47	-0.02	0.08	0.42	0.09	0.22	0.38	0.66	0.85	0.7	1				
DOR2	0.02	0.15	-0.19	0.02	0.23	-0.09	0.09	0.1	0.26	0.48	0.32	0.67	1			
NEW_H9	0.14	0.19	0.09	0.01	0.00	0.11	0.03	0.15	0.25	0.08	0.17	0.16	-0.39	1		
TOTALBTU	0.14	0.33	0.06	0.02	0.2	0.28	0.27	0.33	0.58	0.53	0.56	0.46	0.24	0.02	1	
BTUPRCAP	0.08	0.05	-0.13	-0.01	0.3	-0.54	-0.39	-0.28	0.28	0.26	0.21	0.32	0.28	-0.1	0.59	1

Correlation Matrix of the Variables of Interest

Appendix 4: List and Description of Modeling Variables

Variable Name	Variable Description
EDU2	Highest education completed by householder: 0- No schooling completed 1- High School 2- College 3- Graduate School
HHINC3	2009 gross household income in \$5,000 intervals top-coded at \$100,000+
EMPLOYED	Employment status of householder: 1=Employed (full-time or part-time), 0= Not employed/retired
MALE	Gender of the Householder: 1= Male, 0=Female
MAJORITY	Racial and Ethnic status of the householder: 1=Householder is Non-Hispanic and White only, 0=Hispanic or Non-White
HHSIZE	Number of household members
ADULTS	Number of household members above 19 years old
SPOUSE	Householder lives with spouse or partner
TTSQFT	Total square footage includes all attached garages, all basements, and finished/heated/cooled attics. ²¹
HTYPE	Type of housing unit: 1- Apartment in Building with 5+ Units 2- Apartment in Building with 2 - 4 Units 3- Single-Family Attached 4- Single-Family Detached and Mobile Homes
TOTROM2	Total number of rooms in the housing unit (top-coded at 12 rooms)
OWNED	Tenure type: 1= Owned, 0= Rented
DOR2	Duration or Residence: 1= moved in to the residential location for more than 4 years, 0= lived less than 4 years
NEW_H9	Age of the housing structure: 1=Built after 2000 (less than 9 years), 0=older than 9 years
TOTALBTU	Total energy usage, in thousand BTU, 2009
BTUPRCAP	Total energy usage, in thousand BTU, 2009, divided by household size

List and Description of Modeling Variables

²¹ Total square footage is a measure of home area, ‘enclosed from the weather’. This area, in which energy consumptive activities occur, consists of: ‘attic, basement, garage, and rest of home’. When heated or cooled, the interviewer separately measured each of the four areas. (U.S. Energy Information Administration 2012)

Appendix 5: Acceptable Fit Indices

SEM allows for statistical testing of a postulated theory in a simultaneous analysis of the entire system of variables and causal inter-variable relations. An adequate goodness-of-fit provides support for the plausibility of the hypothesized relationships between variables (Byrne 1998; Dion 2008). However, various researchers use different goodness-of-fit indicators to assess models fit (Schreiber et al. 2006), and fit indices for the model that best represent the data are by no means agreed-upon (Hooper, Coughlan, and Mullen 2008). In contrast with most statistical applications, if the model is correct in SEM, we will not reject the null hypothesis, where the model and observed covariance matrices are equal (Dion 2008).

Available fit indices can be divided into “absolute” and “comparative” fit indices. Absolute fit indices, such as chi-square, demonstrate how well a hypothesized model fits the sample data. Chi-squared is the only inferential statistic, among all fit indices that are descriptive (Iacobucci 2010). Barrett (2007) believes that chi-square is the only substantive test of fit for SEM (Barrett 2007). However, fairly early in the history of SEM, this test fell into disfavor as a test of the absolute fit of a hypothesized model (Hoyle 2012). Chi-squared is sensitive to sample size; “as N increases, chi-square blows up.” (Iacobucci 2010, 91) With a large N, thus, the statistical power of the chi-squared test nearly always rejects the model (Dion 2008; Barrett 2007; Hooper, Coughlan, and Mullen 2008). Further, a main assumption in chi-square test is multivariate normality, therefore, severe deviations from normality can lead to rejection of models that may be properly specified (Hooper, Coughlan, and Mullen 2008). In such cases, model goodness-of-fit based on statistical tests become irrelevant (Barrett 2007).

The earliest alternatives to absolute fit indices are indices that reflect model improvement over the independence/null model (Hoyle 2012). Such fit indices are, therefore, called

incremental/comparative/relative indices, comparing chi-square values between models with a baseline model (Hooper, Coughlan, and Mullen 2008). A drawback of comparative fit indices is that they neither estimate any known population parameters (Bentler 1990), nor follow a known probability distribution (Hoyle 2012). As such, use of such indices to construct formal statistical tests have not been recommended, and instead, rules of thumb govern their use by designating certain threshold for values that can be considered acceptable (Hoyle 2012). Above all fit indices, a model should be grounded in theory and not data-driven:

“When the model is theory based, cross-validated predictive accuracy is even more compelling as the sole arbiter of model acceptability.”(Barrett 2007, 818)

Appendix 6: Sensitivity Analysis

Sensitivity Analysis of the effect of SES on total energy consumption

Changes in the direction and magnitude of the direct effect of SES on total energy consumption, as I decompose the full model, provide useful information about the robustness of the estimates. When this model includes only SES and the total energy consumption index, the direct (and total) effect is significant at positive (0.31) – Figure 30. This simple model fits the data very well (better than the full model). As I add my other social and economic indicators, the magnitude of direct effect from SES on total energy consumption decreases to 0.25, but still positive –Figure 31.

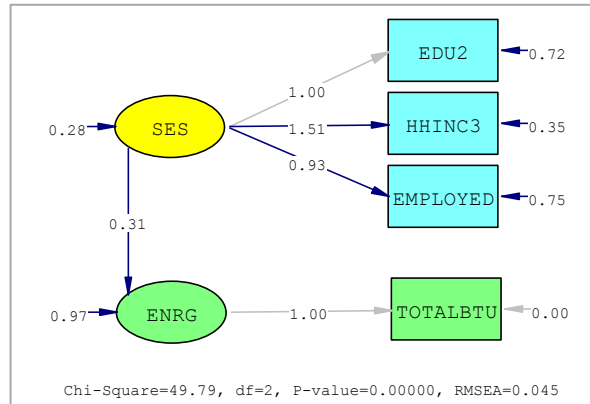


Figure 30. Sensitivity Analysis of the effect of SES on total energy consumption - Model 1

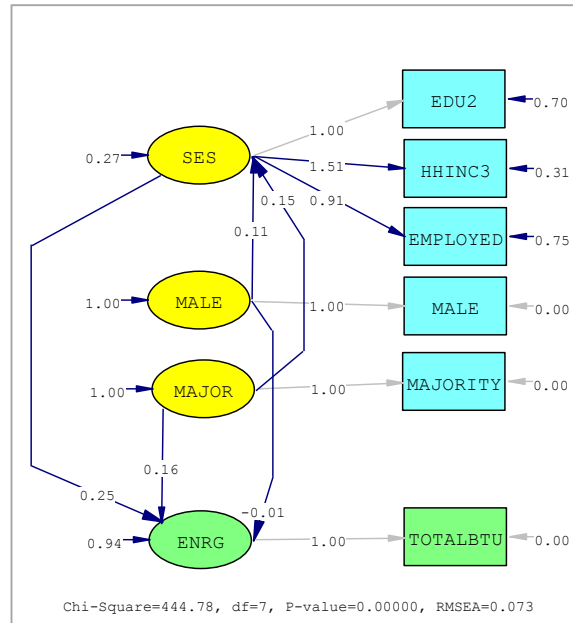


Figure 31. Sensitivity Analysis of the effect of SES on total energy consumption - Model 2

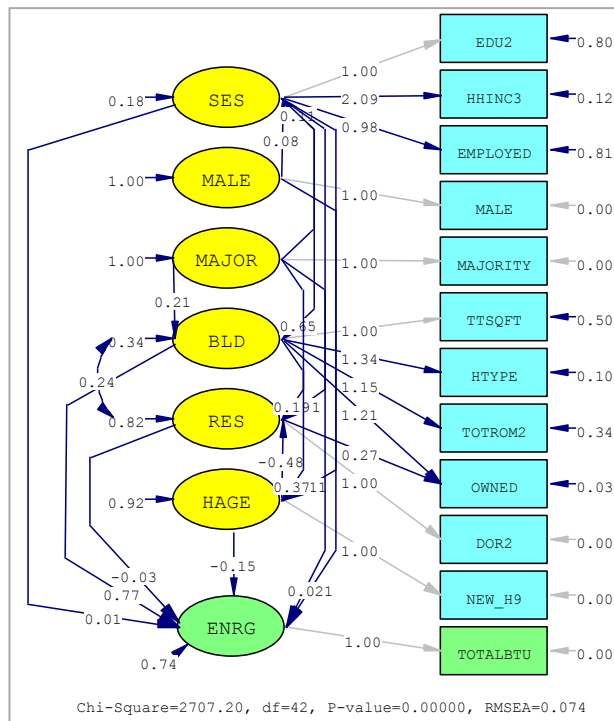


Figure 32. Sensitivity Analysis of the effect of SES on total energy consumption - Model 3

The model in Figure 32 adds the group of housing unit characteristics to the equation. This model shows that the direct effect of SES on energy consumption index decreases rapidly, as

housing unit characteristics are taken into account (0.01, insignificant at $p < 0.05$). The total effect, however, still is 0.45, significant at $p < 0.0001$. In the full model, where I added indicators of housing unit characteristics to the model, the direct effect again becomes statistically significant, but negative (-0.13). Changes in the direct effect of SES on total energy consumption show that this particular effect is sensitive to the existence of BLD (and later on to HHL D) in the model. The total effect, however, has been positive and significant in all models. It seems that SES's direct effect (in the first two models above) carries the portion of its effects that, actually, work through the effects of SES on housing unit characteristics.

Sensitivity Analysis of the effect of HHL D on total energy consumption

Changes in the direct effect of HHL D on total energy consumption during incremental development of the full model provide interesting information. As reported from the full model, HHL D's direct and total effect coefficients on energy consumption are 0.16 and 0.38. When I take out the effect of social and economic indicators from the equation – Figure 33 – HHL D's direct (and total) effect maximizes to 0.52.

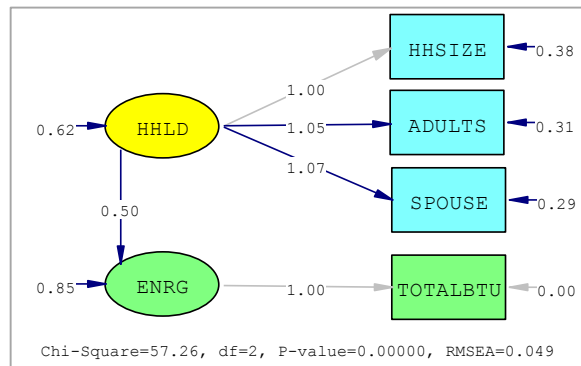


Figure 33. Sensitivity Analysis of the effect of HHL D on total energy consumption - Model 1

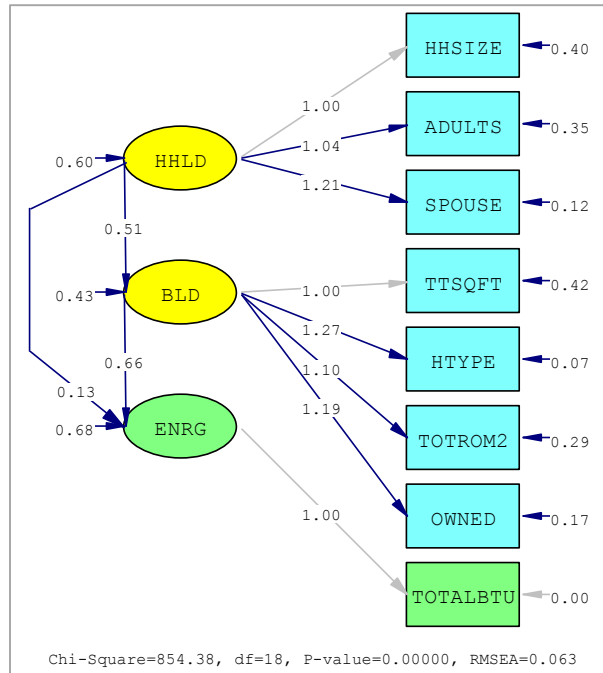


Figure 34. Sensitivity Analysis of the effect of HHLD on total energy consumption - Model 2

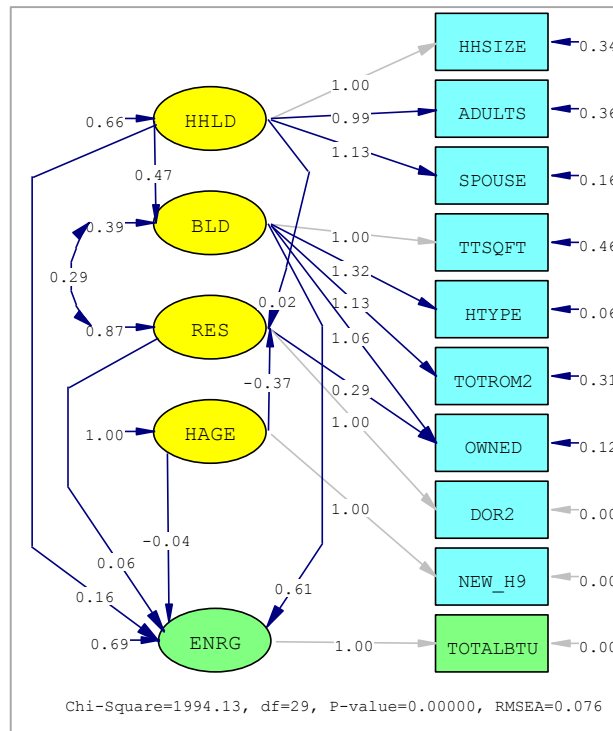


Figure 35. Sensitivity Analysis of the effect of HHLD on total energy consumption - Model 3

The model in Figure 34 reflects the minimum direct effect coefficient for HHLD on total energy consumption, 0.13. However, the total effect is still larger and close to other model

outputs, 0.47. Ultimately, the model in Figure 35 demonstrates the full model without the effect of social and economic indicators. In this model, the direct effect of HHLD on total energy consumption is equal to its coefficient in the full model. The total effect, however, is slightly bigger, 0.45.

Overall, comparing coefficients in the above-mentioned models shows that the total effect of HHLD on energy consumption is to some extent stable, varying around 0.4. Changes in the direct effect, however, provide further testimony for the existence of indirect effects. The three models suggest that, similar to SES, part of HHLD's effect on total energy consumption is through its effects on housing unit characteristics.

Sensitivity Analysis of the effect of BLD on total energy consumption

A closer look at the changes in the direct effect coefficient for BLD (and RES) on total energy consumption provides useful information to assess the robustness of its effect coefficients. In the simplest model, where I only have BLD and ENRG, the direct (and total) effect of BLD on total energy consumption increases up to 0.71 – Figure 36. When I add to this model the RES latent construct, BLD's direct effect decreases by 0.03 from the prior model – Figure 37. Adding HAGE increases the direct effect coefficient (to 0.77), but the total effect still is 0.72 – Figure 38. In all of these models, the effect of RES on total energy consumption is close to zero. The direct effect of HAGE is reasonably close to the full model, -0.15.

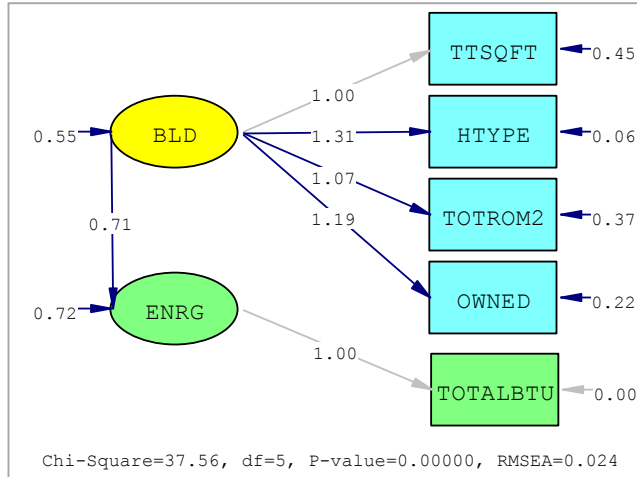


Figure 36. Sensitivity Analysis of the effect of BLD on total energy consumption - Model 1

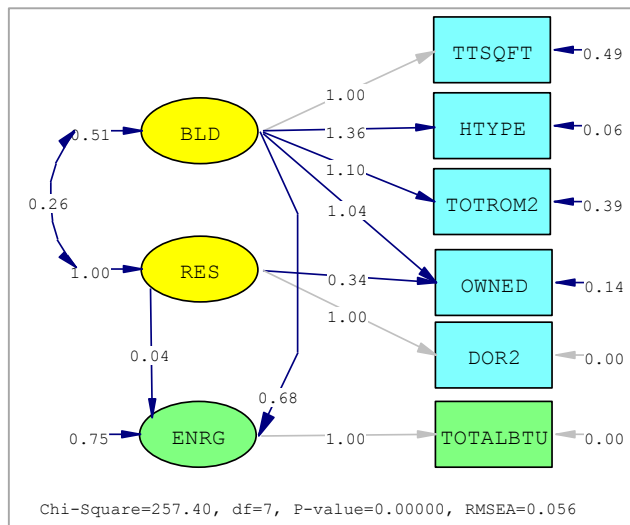


Figure 37. Sensitivity Analysis of the effect of BLD on total energy consumption - Model 2

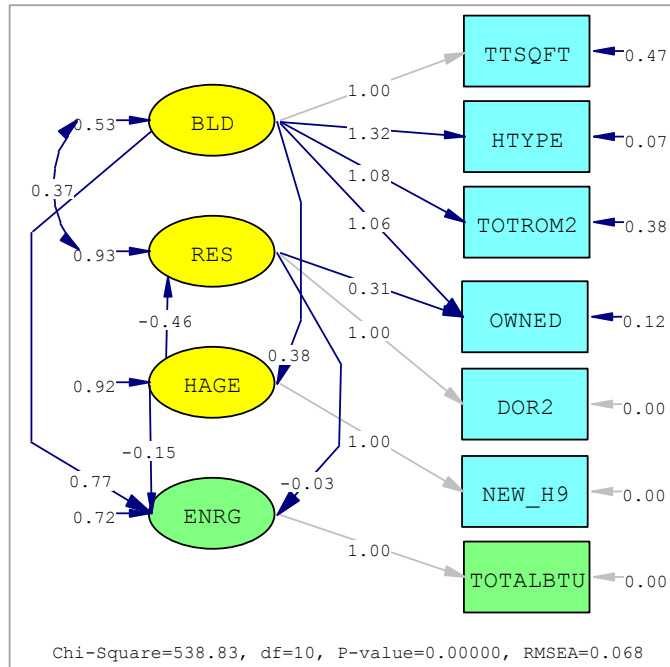


Figure 38. Sensitivity Analysis of the effect of BLD on total energy consumption - Model 3

Adding HHLD to this model, the direct effect of BLD goes down to 0.61 – Figure 35. In this model, the direct effects of RES and HAGE on total energy consumption are close to zero – different from the direct effect of HAGE in the full model and the bottom left model in this footnote. The model in Figure 32 shows that when I substitute HHLD with the group of social and economic indicators, the housing unit characteristics’ direct and total effects are still close to the estimates of the full model. The direct effects for BLD, RES, and HAGE are, respectively, 0.77, -0.03, and -0.15, and the total effects are 0.72, -0.03, -0.13 (all significant at $p < 0.05$). This procedure shows that the effect of BLD on total energy consumption is robust in all models.

Sensitivity Analysis of the effect of SES on Per-capita energy consumption

As I break down the full model, changes in the direction and magnitude of the direct effect of SES on per-capita energy consumption provide useful information for sensitivity analysis. When I only have SES and per-capita energy consumption in my model, the direct (and total)

effect is considerably smaller than the corresponding direct effect coefficient in the full model (-0.17 vs. -0.54) – Figure 39. When I add my other social and economic indicators, the magnitude of effect for SES on per-capita energy consumption increases to -0.31 – Figure 40.

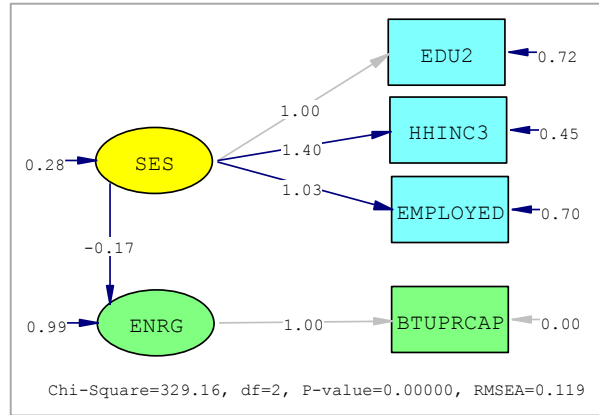


Figure 39. Sensitivity Analysis of the effect of SES on Per-capita energy consumption - Model 1

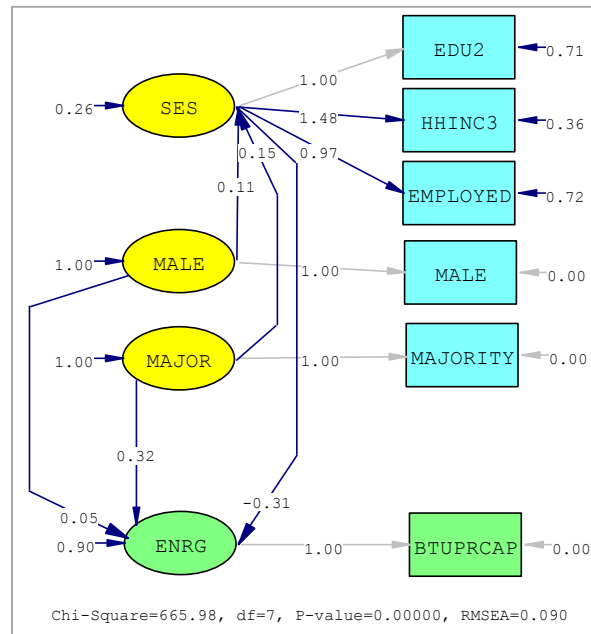


Figure 40. Sensitivity Analysis of the effect of SES on Per-capita energy consumption - Model 2

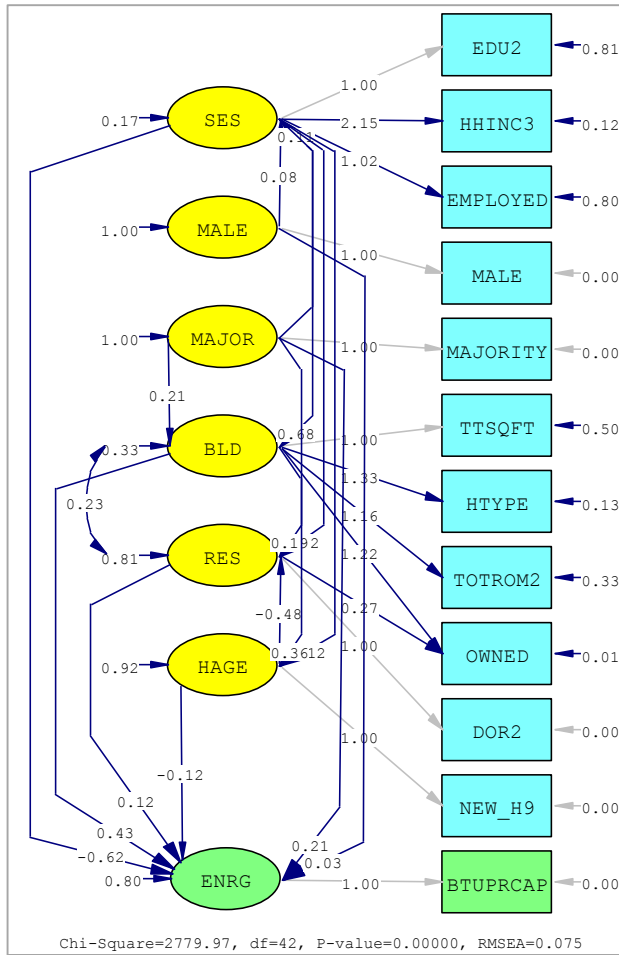


Figure 41. Sensitivity Analysis of the effect of SES on Per-capita energy consumption - Model 3

None of the two models fit the data as well as the full model does, unlike the total model. The model in Figure 41 adds up the group of housing unit characteristics variable to the previous model. This model shows that the direct effect of SES on the energy consumption index is -0.62, which is slightly more than the coefficient in the full model. The total effect, however, is -0.33, significant at $p < 0.0001$. Overall, all three models show that the total effect of SES on per-capita energy consumption is negative, and robust. The total effect coefficient varies between -0.17 to -0.33, with the full model estimating it at -0.22.

Sensitivity Analysis of the effect of HHLD on Per-capita energy consumption

Changes in the direct effect of HHLD on per-capita energy consumption during incremental development of the full model provide interesting information for sensitivity analysis. In the simplest form, the direct (and total) effect of HHLD reduces to -0.41, compared with the full model – Figure 42. When I add BLD to the model, the direct effect of HHLD on per-capita energy consumption increases in magnitude to -0.75 (Figure 43). The total effect, however, is -0.37.

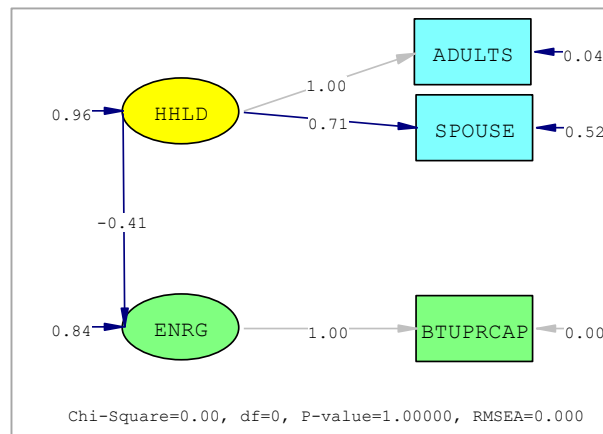


Figure 42. Sensitivity Analysis of the effect of HHLD on Per-capita energy consumption - Model 1

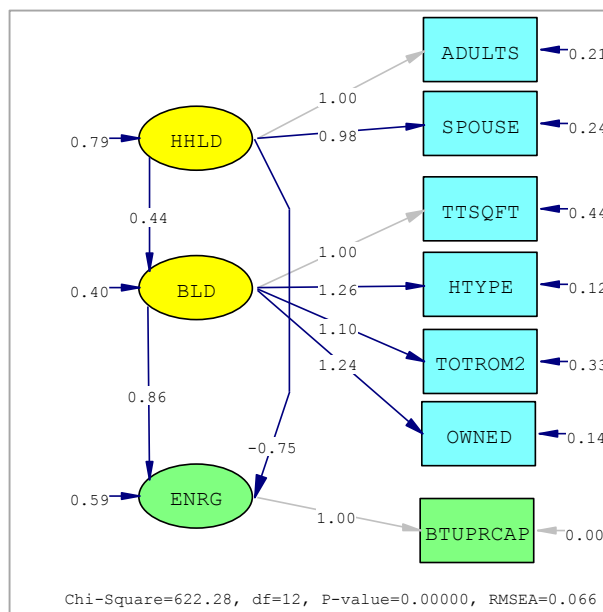


Figure 43. Sensitivity Analysis of the effect of HHLD on Per-capita energy consumption - Model 2

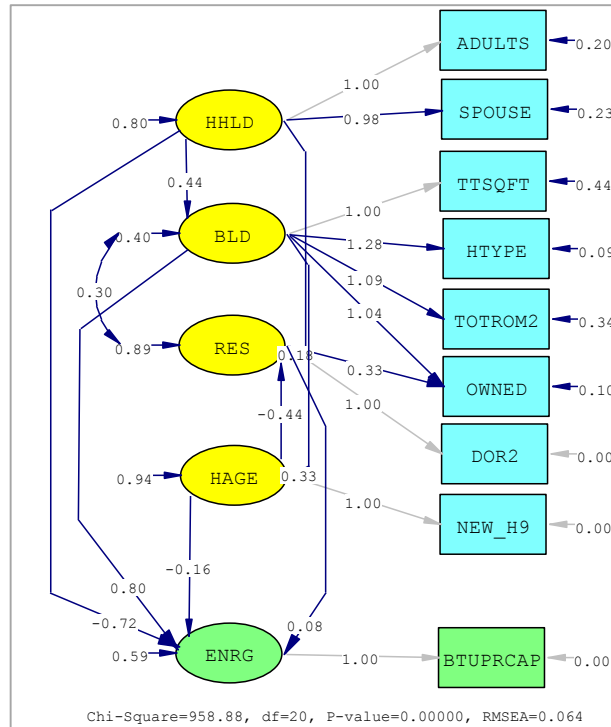


Figure 44. Sensitivity Analysis of the effect of HHLD on Per-capita energy consumption - Model 3

Adding other housing unit characteristics from the full model – Figure 44 – the direct effect of HHLD remains almost the same (-0.72). The total effect on per-capita energy consumption is similarly close to the previous model (-0.34). In all models, the direct and total effects of HHLD on per-capita energy consumption are negative, which is not surprising, and seem to be robust.

Sensitivity Analysis of the effect of BLD on Per-capita energy consumption

To check the robustness of the effect estimates, I review coefficients in smaller/simpler models. The smallest/simplest model with only BLD and the per-capita energy consumption as outcome variable – Figure 45 – shows a smaller magnitude of effect (0.43), compared with the full model. As I add the residency status latent construct to the smallest/simplest model, the direct effect of BLD decreases, even more, to 0.26 – Figure 46. In this model, the effect of residency status on the energy consumption index is almost 3 times larger than its effect in the full model (0.22 vs. 0.08). Adding HAGE increases the direct effect coefficient for BLD

from the prior model to 0.34, with a total effect of 0.27, which is close to the effect of BLD in the prior model – Figure 47. The effect of RES is now twice the size of its corresponding effect in the full model (0.15 vs. 0.08). The direct and total effects of HAGE are similar to the full model (DE: -0.14 vs. -0.13, TE: -0.18 vs. -0.20).

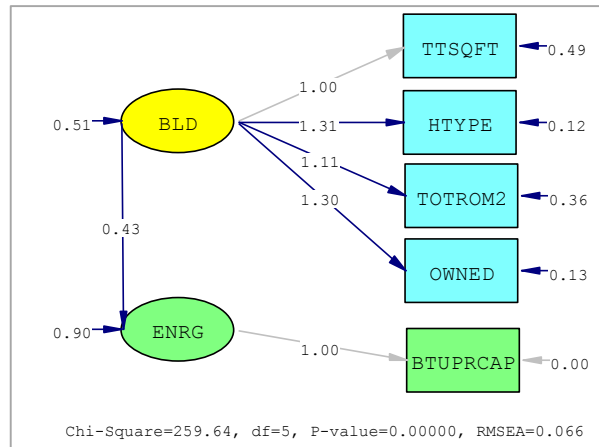


Figure 45. Sensitivity Analysis of the effect of BLD on Per-capita energy consumption - Model 1

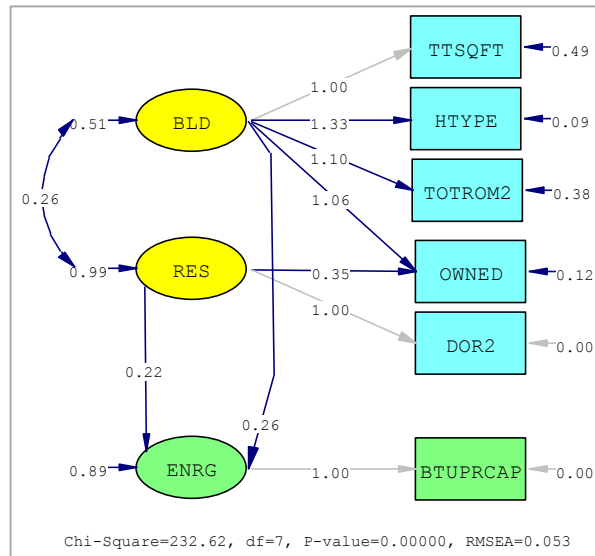


Figure 46. Sensitivity Analysis of the effect of BLD on Per-capita energy consumption - Model 2

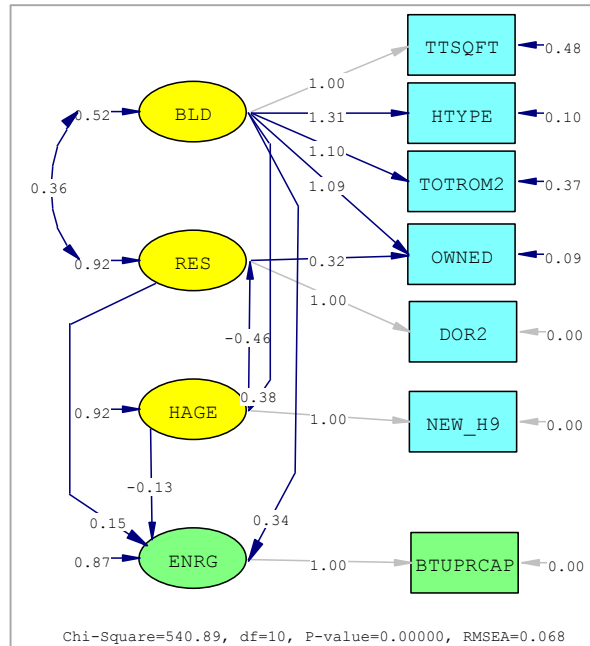


Figure 47. Sensitivity Analysis of the effect of BLD on Per-capita energy consumption - Model 3

The model in Figure 44 showed that by adding HHL D to the previous model, the direct effect of BLD increases considerably to 0.8 (TE: 0.74), the direct effect of RES drops to 0.08, and HAGE's effect becomes -0.16 (TE: -0.19). Substituting HHL D with the group of social and economic indicators (Figure 41), the direct effect of BLD on per-capita energy consumption decreases to 0.43 (TE: 0.74), the effect of HAGE decreases to -0.12 (TE: -0.19), and direct effect of RES only increases slightly to 0.12 (TE: 0.08). Overall, changes across models demonstrate that as I add the effect of household characteristics, and social and economic indicators to the model, the direct effect of building characteristics on per-capita energy consumption increases. Such an increasing effect clearly demonstrates that part of the building's large direct effect on per-capita energy consumption is HHL D and SES effects that are being carried through BLD.

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