Implications of Consumer Lifestyle Changes and Behavioral Heterogeneity on U.S. Energy Consumption and Policy

Ashok Sekar
axs5498@rit.edu

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Implications of Consumer Lifestyle Changes and Behavioral Heterogeneity on U.S. Energy Consumption and Policy

By
Ashok Sekar

A DISSERTATION
Submitted in Partial Fulfillment of the Requirements for the Doctor of Philosophy in Sustainability

Department of Sustainability
Golisano Institute of Sustainability
Rochester Institute of Technology

Aug 12, 2017

Author: ________________________________
Sustainability Program

Certified by: ____________________________
Dr. Eric Williams
Associate Professor, Sustainability

Certified by: ____________________________
Dr. Roger Chen
Associate Professor, Sustainability

Approved by: __________________________
Dr. Thomas Trabold
Associate Professor and Head, Sustainability Department

Certified by: ____________________________
Dr. Nabil Nasr
Assistant Provost and Director, Golisano Institute for Sustainability and CIMS
Committee Approval:

Submitted by Ashok Sekar in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Sustainability and accepted on behalf of the Rochester Institute of Technology by the dissertation committee.

We, the undersigned members of the dissertation committee, certify that we have advised and/or supervised the candidate on the work described in this dissertation. We further certify that we have reviewed the dissertation manuscript and approve it as partial fulfillment of the requirements of the degree of Doctor of Philosophy in Sustainability.

Approved by:

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<td>Eric Hittinger, Committee Member</td>
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<td>Pengcheng Shi, Committee Member and Exam Chair</td>
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ABSTRACT

Understanding the relationship between consumer lifestyle and energy use is essential to solving many of the energy and sustainability challenges. By studying shifts in consumer lifestyle over time and behavior heterogeneity, this dissertation provides valuable insights into understanding energy consumption trends and improving energy efficiency programs.

Technologies continue to change our daily lifestyles, influencing energy demand. In the first part of the dissertation, changes in how people spend their time (time-use) patterns are used as an indicator of lifestyle shifts. Using decomposition analysis changes in energy use due to these lifestyle shifts are measured. The results show that for an average American, time spent in residences increased at the rate of 3.1 minutes per day per year while time spent for travel and other non-residential activities decreased (-0.4 min/day/year and -2.7 min/day/year respectively). The time-use shifts induced a net energy change of -1,722 trillion BTU, 1.8% of national primary energy consumption in 2012. The lifestyle/energy shifts are interpreted as primarily driven by information and communication technology: people are spending more time at home with online entertainment and services.

Information provided to consumers and energy efficiency rebate programs generally assume characteristics of an average consumer. There is, however, substantial heterogeneity in behavior, energy prices and impacts of electricity use. To understand the impact of heterogeneity on rebate programs, in the second part, the economic and carbon benefits of efficient choices of three household technologies (television, clothes washer and dryer) are assessed for different locations and usage patterns. For some households, an efficient energy washers and dryers do not save money, but brings substantial economic benefits to others. Viewing utility appliance rebate programs as tools for carbon abatement, abatement cost of carbon was assessed. At current rebate levels, for an average household, the abatement cost for carbon exceeds social cost of carbon (SCC). However, subpopulations with abatement cost less than SCC exists: 4%, 6%, and 41% for televisions, washers and dryers respectively. Therefore, abatement programs can benefit from targeted intervention.

For targeted intervention, it would be useful to identify groups with high energy use and characterize their demographics. To achieve this, in the third analysis, time-use survey data is
used to characterize patterns of TV watching. Using cluster analysis, the population was divided into three groups, the high-energy use cluster has 14% of the population and spends an average of 7.7 hours per day on TV. This relatively small group, due to high use, accounts for 34% of total television energy consumption. This group tends to be older, not in the work force and/or poorly educated. A high-use household purchasing an efficient television saves more than three times the energy of an average household.

The main policy implications of these results are that more targeted information and policies have potential to enhance adoption by household who will benefit the most economically as well as reduce more carbon. In the management of utility efficiency programs, the results make a case for variable rebates or tiered communication programs.
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Chapter 1: Introduction

1.1 Background

Understanding the relationship between consumer lifestyle and energy use is essential to solving many of the energy and sustainability challenges. According to (Bin and Dowlatabadi 2005), consumer lifestyle choices drove more than 80% of all energy demanded and CO₂ emissions in the U.S for the year 2005.

Technology advancements are occurring at a rapid pace and they impact lifestyle choices. Information and communication technologies (ICT) along with the power of the internet has enabled numerous alternative lifestyle choices some of which has huge implications on energy demand. Ride sharing apps such as Uber and Lyft and other similar services have negated the demand for new automobiles, increased vehicle occupancy and reduced congestion (Alonso-Mora et al. 2017; Li, Hong, and Zhang 2016). E-commerce has not only displaced numerous trips to a “click” in a computer, many retailers are closing their brick and mortar stores. Mitigating energy use and carbon requires measuring and understanding them. Therefore, measuring the pace of lifestyle changes and quantifying lifestyle change induced energy change is essential. If measured accurately, the relationships can also aid in energy forecasting since popular energy forecast models such as, National Energy Modeling System (NEMS) does not include the influence of these technology on energy forecasts.

Heterogeneity in consumer lifestyle is another important topic not well characterized in the literature but have significant influence in energy modeling and policy. Consumers having larger energy saving potential are more economically motivated to adopt an energy efficiency or advanced technology compared to their counterparts. Heterogeneity of energy consumption can be large. Across the U.S. the variability can be larger, for single family households, the energy consumption BTU per square foot varied between 1 and 500 (EIA 2012; Lutzenhiser, L. and Bender, S. 2008). Despite the variability most energy models and policy is based on the assumptions of an average consumer, leading to devising policies that are inefficient. According
to (Allcott et al. 2015), policies that do not target consumer based on their energy saving potential can lead to welfare loss.

1.2 Motivation

Research in consumer behavior shifts and heterogeneity are acutely limited by the data. Despite the data constraints, many researchers used surveys supplemented with novel methods to understand consumer effects on energy use. In the case of establishing the link between lifestyle and energy use, public data such as consumer expenditures and time use data have been supplemented with methodologies such as consumer life cycle approach (cLCA) (Bin and Dowlatabadi 2005; Schipper et al. 1989). Although literature on linking lifestyle to energy consumption exists, no research has quantified the shifts in lifestyle and their associated energy demand change across the U.S. Availability of multi-year time use data (how and where people spend their time) provides an opportunity measure lifestyle shifts as a function of time use. When this approach is supplemented with decomposition analysis energy shifts due to lifestyle can be established.

Billions of dollars of tax money are spent in incentivizing U.S. consumers to adopt energy efficient technologies with goals of mitigating energy and carbon. However, these programs do not target participants based on their potential energy or carbon savings. Given large consumer heterogeneity, it is important to identify consumers that contribute to the policy goals at the cheapest cost and target them. Large body of research about the effects of consumer heterogeneity and its impact on solar PV and alternative vehicles rebate policy exists. (Holland et al. 2015) showed that the federal subsidy of $7500 for electric vehicles is a net welfare loss to the society. However, in the case of residential energy efficiency programs no such research exists. With data on consumer behavior available through national surveys such as Residential Energy Consumption Survey (RECS), there is a clear opportunity to measure effect of heterogeneity on residential energy efficiency programs.

1.3 Research Objectives

This dissertation aims to contribute to the broader understanding of consumer lifestyle shifts and consumer heterogeneity on energy by answering two specific questions.
1. How has consumer lifestyle, measured in terms of time use, changed over the years and what is the relationship between lifestyle changes and energy shifts.
2. How heterogeneous are residential consumers and how does their heterogeneity impact energy efficiency policy programs, especially appliance rebate programs. And, how to identify high-energy use consumers and characterize their demographics.

1.4 Dissertation outline

The dissertation is divided into 5 chapters. This chapter provides a brief background on the importance of studying consumer lifestyle shifts and heterogeneity. Chapter 2 examines the effect of lifestyle shifts on energy consumption. Chapter 3 focuses on quantifying the effect of consumer heterogeneity on energy efficiency measures via a case study for televisions, washers and dryers. Chapter 4 evaluates a method for identifying high energy use consumers from time-use data and characterize their demographics through a case study for televisions. Finally, chapter 5 summarizes the conclusions of the dissertation and discusses future work.
Chapter 2: Decomposing the effects of time-use shifts on energy consumption

Chapter Summary

Lifestyles are changing due to Information Technology and other socio-technological trends. I attempt to capture the energy effects of the time-use aspects of lifestyle changes. I use the American Time Use Survey (ATUS) to first find shifts in times performing different activities from 2003–2012. The results show that an average American spends more time in residences (19 more hours per year). This increased home time is balanced by decreased time spent for transportation (3 hours per year) and in non-residential buildings (16 hours per year). Increased residential time is mainly due to more work at home, video and computer use, reduced time in commercial buildings is mainly due from shifting work to home and less retail shopping. Decomposition analysis is then used to estimate effects on energy consumption. The model indicates that time-use changes reduced national energy demand by 1,700 trillion BTU over the decade, 1.8% of the national total.
2.1 Introduction

Despite substantial improvements in energy efficiency, energy demand has increased around the world in the last several decades. In the U.S. total residential energy use increased 39% from 1975 to 2015, with a per capita decrease of 6% ("Total Energy - U.S. Energy Information Administration (EIA)" 2016). Over the same time period, transportation energy use increased 52%, with a per capita increase of 3%. Mitigating consumption is a critical strategy to manage the societal challenges of energy, many argue that improving efficiency is more economically effective than changing the energy supply (Naucleér and Enkvist 2009; Real Prospects for Energy Efficiency in the United States 2010).

Mitigating energy use is supported by measuring and understanding it. Lifestyle is integrally tied with energy demand (Bin and Dowlatabadi 2005; Schipper et al. 1989). One aspect of lifestyle is the spending of money to buy things. What products are bought is important to energy use, e.g. the size of home or efficiency of a vehicle. The ownership and efficiency of energy using products changes is relatively well understood. Various datasets have been developed (EIA 2012; Santos et al. 2011; EIA 2016) and many analyses done to understand the trends in how population, ownership and efficiency interact to influence energy demand (Hojjati and Wade 2012b, 2012a; Lakshmanan and Han 1997; Jalas and Juntunen 2015).

Another facet of lifestyle is how people spend their time, i.e. what activities they do and where. Activity choices influence energy use over multiple sectors. For example, a person retiring no longer requires an office, is likely to travel less and spend more time at home, affecting energy use in commercial, transport and residential sectors respectively. How lifestyle changes affect energy use across sectors is not understood and potentially an important consideration in apprehending consumption trends. Information and communication technology (ICT) is surely one of the most important drivers of recent changes in lifestyle. Using ICT, people are presumably at home more watching big screen televisions, on the computer doing online shopping, or even working from home. As vacant shopping malls and movie theaters around the nation attest to, increasing some activities must lead to decrease in others.
In this article, I address this gap by studying changes in time-use and its effects on energy in different sectors. Our focus is on the U.S. partly because it is large country with large energy demand and also because there is a publicly available database to leverage: The American Time Use Survey (ATUS). The Bureau of Labor Statistics has conducted the ATUS annually for over a decade (BLS 2015b), querying over 11,000 Americans each year on their daily schedule of what activities were done and where. Many other nations also conduct time use surveys (Time-Use Measurement and Research: Report of a Workshop 2000), the U.S. version has the virtue that the micro-data are publicly available.

I first analyze the time use surveys to determine trends in how Americans are spending their time. This is done via linear regression of total time use per day for separate activities such as working, sleeping, computer use and socializing, over the period 2003-2012, a time period chose to match availability of energy data. I also track locations where activities were done, e.g. an aggregate increase in telework would be represented by some minutes per day less time working at a workplace and more minutes per day working at home. The constancy of time has a powerful utility: Any increase in any activity must be accompanied by corresponding decreases elsewhere. Note that drivers of changes in time use can work over different time scales. ICT and aging society are longer term effects, economic cycles can shift time use over several year cycles shifting a part of the population between employed and unemployed. I analyze study both aggregate and sub-populations (e.g. employed, retired and not-in-labor force) populations to help clarify the longer-term trends.

The second and more challenging part of the analysis is to relate changes in time-use to shifts in energy consumption. I address this with a decomposition analysis of national energy consumption in residential buildings, transport, and commercial (and public buildings). Decomposition analysis partitions an overall change in energy use into contributions from individual factors such as population, efficiency, and others. Analysts have long used decomposition analysis to study the structural changes of national level and sector level energy consumption (EIA 2015a; Feng et al. 2015; Hoekstra and Bergh 2002; Hojjati and Wade 2012b, 2012a; Weber 2009; Lakshmanan and Han 1997; Unander 2007; Nie and Kemp 2014; IEA 2012). I add time use as an additional descriptor to other drivers of energy use, such as population, area (of buildings) and efficiency.
The model accounts for how changes in time spent in different classes of buildings and vehicles affects energy use. The model does not account for interactions not mediated by time use, in particular the additional electricity consumption of data centers induced by residential demand for the Internet. Supply chains for changes in production associated with lifestyle changes are also not included, e.g. for consumer electronics. Future models should account for such factors. Later in the article I argue that the decomposition analysis based on time-use captures important aspects of changes in energy use due to lifestyle changes.

While a relatively unexplored area, there are prior studies linking time-use and energy consumption (Jalas 2005; Jalas and Juntunen 2015; Schipper et al. 1989; Druckman et al. 2012). This is however the first paper to disentangle the contribution of time-use changes on energy demand across multiple sectors. The critical issue explored here is how lifestyle changes can increase some energy uses while decreasing others. I provide a holistic though aggregate accounting of how these changes combine. Note that for vehicle use, time spent in a vehicle is closely tied to vehicle miles travelled, which is well studied (BTS 2016) and incorporated into energy demand modeling (EIA 2015b). Notably, vehicles miles per person in the U.S. increased steadily from 6,200 miles in 1975 to a peak of 10,100 miles in 2008, after which falling slowly, with a level of 9,500 miles in 2014 (“Office of Highway Policy Information - Policy | Federal Highway Administration” 2016). While it is not yet clear to what degree travel is stabilizing versus decreasing, there is clearly a new regime from the early 2000s breaking the steady increase of previous decades. While the new trajectory in vehicle use is promising, it is important to understand it in a larger context.

The results, detailed below, show that time-use changed significantly in the U.S. from 2003-2012, with people spending more time at home, driving and spending time in commercial buildings correspondingly less. The model suggests that Americans are saving energy by spending more time at home. While energy use at home increased, this came along with reduced driving (the most energy intensive activity per minute) and operating fewer commercial buildings, primarily offices and retail shopping.
2.2 Methods

Observed energy trends between 2003 and 2012 are decomposed into time use and non-time use factors using a popular technique called Log Mean Divisia Index Method I (LMDI-I) (B. W. Ang 2005). The non-time use factors include population trends, changes in building area, and energy intensity trends. The contribution of the factors to total energy use trends are compared within and across three sectors viz., residential, non-residential and transportation. The sectors are defined based on activity location. Along with decomposition analysis, time use trends are also summarized for average American and subpopulations based on employment characteristics and age.

2.2.1 American Time Use Survey (ATUS).

The American Time Use Survey (ATUS) informs how people allocate their time during a 24-hr day. ATUS is an annual survey conducted by the Bureau of Labor Statistics (BLS) since 2003. Respondents for the survey are 15 years and older. Annual participation in the survey exceeds 11,000 respondents each year. Only one household member is sampled per household. The survey is conducted using computer-assisted telephone interviewing (CATI) in which the participants respond on how they spent their time on the previous day, the location of their activity, and information about people they were with when performing the activity. Conducting the survey via a conversational interviewing style mediated by an expert is assumed to improve reporting accuracy. In addition to the activity information, ATUS also collects respondent's household level socio-economic data such as age, income, sex, race, marital status, education level, employment status and many others. The ATUS website provides more information about the survey (BLS 2015b).

Information about activity location in ATUS enables categorization of activities into sectors (residential, non-residential and transportation) enabling a sector-level analysis. Activities categorized as Residential include activities performed at the respondent’s or someone else’s home. Personal care activities such as sleeping and grooming oneself, which did not contain locational data due to privacy concerns, were also categorized as residential. The non-residential sector comprises of all activities performed in a commercial space such as the workplace, school, malls and grocery stores and other outdoor spaces. The transportation sector includes travel in a
personal vehicle (car, motorcycle, or truck) as a driver or passenger. Other travel modes such as walking, cycling and public transportation were not included in this sector because our goal is to link automobile time use to energy use. The category other includes various travel modes not covered in the transportation sector, and activities for which location information was ambiguous and not specified.

Of the 1,440 minutes in a day, average American spends 74% of their time doing activities in the residential sector followed by 21% in non-residential and 4.3% in the transportation sector. At home, most of the time is spent sleeping (523 minutes a day) and watching television (163 minutes a day). In the non-residential sector, average American spends most time at their workplace (179 minutes a day) followed by school (23.8 minutes a day), restaurant or bar (17.5 minutes a day) and others. Driving to work consumes the largest travel time followed by traveling to purchase gas.

To explain the change in lifestyle over the years (2003-2012), I use a linear model, where activity time is a function of the year the activity is performed to estimate the change in time spent of an activity in minute per day per year. I only report on time use changes that are at and above 90% confidence.

2.2.2 Other Data for Decomposition.
The data for decomposition analysis such as population, area, and primary energy demand in each sector are obtained from public sources. The EIA provides the primary energy consumption and building area data for residential and non-residential sectors(EIA 2015b). I use commercial sector energy consumption as the proxy for the non-residential sector. The commercial sector as defined by the EIA does not account for energy demanded by outdoor recreational areas which are included in the non-residential sector as defined based on ATUS. As the energy consumed in recreational areas is negligible compared to other commercial spaces they are neglected. The transportation sector accounts for personal vehicles such as cars, motorcycle, and trucks. Bureau of Transportation Statistics (BTS) provides energy consumption of personal vehicles through categories Light duty vehicles(BTS 2016). Census Bureau provides population statistics(US Census Bureau 2015). Fig. 5 summarizes the data trends between the years 2003 and 2012.
While ATUS data is available until year 2015, due to unavailability of commercial sector occupied building area for any year after 2012, I limit our study between the years 2003 to 2012.

Figure 2-1 Input data for the decomposition analysis, 2003-2012: a) sector-by-sector primary energy consumption. b) U.S. population and c) occupied building areas in residential and commercial sectors. Data sources: (EIA 2015b; US Census Bureau 2015; BTS 2016)

2.2.3 Decomposition Analysis.

Decomposition analysis is concerned with decomposing a trend in an aggregate indicator into contributions from underlying factors. For example, a decomposition of residential sector energy consumption may involve capturing three effects viz., activity, structure and intensity effects. The activity effect captures the change in population in the household sector. The structure effect captures the change in the mix of activities within the sector, floor area per population, and the intensity effect captures the energy use per floor area.

Decomposition analysis finds its basis in the index number theory that is used to study price and quantify effects on total consumption of goods(Boyd and Roop 2004). It has been widely used in many fields including, but not limited to, energy, logistics, and emissions at various levels

There are many methods for decomposition although, all those methods can be classified into one of two techniques: Laspeyres index and Divisia index(B. W. Ang 2004). In the Laspeyres index based methods the contribution of any factor to the change in an aggregate indicator is quantified by letting the factor in question change while holding all other factors constant. In other words, a factor's effect is calculated as a function of the factor’s percentage change. For Divisia index based methods, a factor's contribution is measured as a function of the factor's logarithmic change. Further, depending on how change in aggregate indicators are measured decomposition methods can be classified into additive or multiplicative decomposition. Additive technique supports decomposing the change measured as the difference. Multiplicative decomposition is used when change is measured as ratio. Given n factors mathematical representation of additive decomposition is shown in Equation 1.

\[
\Delta E = E^{t_2} - E^{t_1} = \Delta V_1 + \Delta V_2 \ldots, \Delta V_n + V_{rsd}
\]

where \(\Delta E\) is the change in aggregate indicator measured as difference between two time periods \(t_1\) and \(t_2\). \(\Delta V_1, \Delta V_2 \ldots, \Delta V_n\) are the underlying \(n\) factors changes and \(V_{rsd}\) is the residual. In the case of Divisia based methods factor effects are quantified using the formula: \(\Delta V_n = \sum_{i=1,2...n} w_n \times ln\left(\frac{v_i^{t_2}}{v_i^{t_1}}\right)\). Where, \(w_n\) is a weighting function that varies depending on the approach used.

In this paper, the Log Mean Divisia Index method I (LMDI-I), a divisa index based additive decomposition technique is used(B. W. Ang 2005). The basic form of LMDI-I is similar to equation 1 explained above. The weighting used in this method is Logarithmic mean of the change in the aggregate indicator (\(E\)). Researchers recommend LMDI-I for general use because of its theoretical soundness, ease of use and adaptability(B. W. Ang 2004; B. W. Ang and Liu 2007). LMDI-I has the virtue of leaving no residuals, easing interpretation of factor effects.
Further, a direct and simple association exists between additive and multiplicative forms of the LMDI-I method. Therefore, researchers who conduct meta-analysis and other review studies can easily translate additive forms to multiplicative or the vice versa. Decision makers have widely used this method in various capacities. Ang et al. (2010)(B. W. Ang, Mu, and Zhou 2010) reports LMDI techniques were used by government organizations from many countries including the USA, Canada, New Zealand and Australia. Recently international organizations such as the International Energy Agency (IEA) have also adopted this technique(IEA 2012).

For residential and non-residential buildings, I decompose sector-wise energy changes into four factors: Population, area, intensity and time. For the transportation sector, I decompose energy changes Population, intensity and time. As the name implies, population and time effects are captured as the energy change due to population and time use trends in each sector. Area effect represents the change in area per capita in each sector. And finally, the intensity effect captures all the other changes not modeled explicitly for each sector that includes efficiency upgrades. It is measured as energy per unit area per time. The following equations (2) and (3) captures our modeling framework.

\[
\Delta E_k = \text{Population effect} + \text{Area effect} + \text{Intensity effect} + \text{Time effect} \quad (2)
\]

\[
\Delta E_k^{\text{time use}} = \frac{(E_k^{t_2} - E_k^{t_1})}{\ln \left( \frac{E_k^{t_2}}{E_k^{t_1}} \right)} \left[ \ln \left( \frac{P^{t_2}}{P^{t_1}} \right) + \ln \left( \frac{A_k}{P} \right)^{t_2} \right] + \ln \left( \frac{E_k}{A_k^2(T_k^{t_2})} \right) + \ln \left( \frac{T_k^{t_2}}{T_k^{t_1}} \right) \quad (3)
\]

where, \( \Delta E_k \) is the change in energy consumption in each sector \( k \), over the years 2003 \((t_1)\) and 2012 \((t_2)\). \( P \) is the U.S. national population and it does not vary by sector. \( A \) is the area of building space for residential and commercial sector. Lastly, \( T \) is time spent in each sector. In transportation, time use in vehicles can be compared to vehicle miles traveled.

It is important to understand if accounting for time-use gives qualitatively different results from prior studies that did not account for it. Therefore, two decomposition analyses are conducted for each sector with and without time use effect. In the case of decomposition without time effect the intensity effects also comprises of time use changes. By comparing the intensity effect between
the two versions importance of time use is determined. Equation 4 shows the mathematical form for residential and non-residential sector. In the case of transportation sector, the area effect is not included.

The obvious differences between the model presented above and those discussed in the literature is explicitly quantifying time use factor. There are other differences, decomposition analysis performed by IEA (2012)(IEA 2012) and many others identifies three underlying factors for energy consumption activity, structure and intensity. However, those studies disaggregate the sectors into many subsectors and the contribution of activity shifts between the subsectors are measured as the structure effect. Subsector for residential sector are, space heating, water heating, cooking, lighting and appliances. Further, intensity effect at a subsector level is also measured. Other researchers identify more than three non-time use factors (Hojjati and Wade 2012b; EIA 2015a; Hojjati and Wade 2012a). While there is opportunity to perform a more detailed analysis, given the scope of this paper, i.e. decomposing time-use effect, a more granular study is a future work.

2.3 Results

2.3.1 Trends and status in activity times.
To understand trends in activity times, from ATUS I derived a dataset describing total time for individual activities by year and analyzed using a linear regression model for each activity. The slope of the regression reflects the rate of change in activity time, the intercept is modeled value of total hours per day for the year 2003. Figure 1 shows the results for an average employed American including both weekends and weekdays. The employed population was chosen to control for economic up and down-turns. Only activities with statistically significant changes (90% confidence) are shown therefore hours per day, on the right, totals 18.1 hours (out of a 24-hour possible total), representing 75% of a day. Non-residential locations are commercial and public buildings and outdoors, the last representing a very small portion of time spent on average.
To first discuss total time use, unsurprisingly, sleep and work are the two activities with the highest values. Total work is 5 hours/day in 2003 (4.7 hours/day at the workplace, 0.3 hours at home) differing from the usual “8 hours/day” because weekends and part time workers are included. Television, which includes watching videos on other devices, is the most popular other activity at 2.1 hours/day.

To next discuss changes in time use, most of the trends appear attributable to adoption of ICT. Time spent on television watching and computer use increased. Total time working did not change much, but there was ~7 hours per year switch from workplace to working at home. Time spent shopping on non-food/fuel items went down, presumably due to e-commerce. Total sales through the internet grew more than 3 times between the years 2005 and 2015 (US Census Bureau 2016). Travel time went down by 1.93 hours per year. The decrease in travel time mirrors the reduction of total vehicle miles traveled per year in the U.S (BTS 2016).
2.3.2 Trends and status in locations of activities

Next, I analyze trends and state in where people spend their time (at home, in a vehicle, or in a commercial/public building) from 2003-2012. Location is important for energy use because increased/reduced time spent at home/in a vehicle or other building corresponds to increased/decreased energy use. As before, a regression model of total time per year yields a slope for the change in time use and intercept for modeled value in 2003. I consider both the aggregate and sub-populations of different work status and age. The Employed group consists of both full-time and part-time employees. Respondents not in labor force consist of students, household members taking care of children and others. Fig. 2 shows the results.

The average American during a typical day (weekday and weekend) in 2003 spends 17 hours in their or others’ residences, 1 hour in travel and 5 hours in commercial and public buildings. Over the decade time spent at home increased by 19 hours per year, while time spent elsewhere decreased. Time spent traveling and time at non-residential spaces reduced by 3 and 16 hours per year respectively. Over a decade these values translate to 190 additional hours at residence at the expense of time spent elsewhere equaling 30 hours in transportation and 160 hours of non-residential time.
By and large, time use trends for subpopulations are similar to patterns observed for the average population. However, there are two intriguing exceptions. First, the population aged between 18 and 24 shows a more dramatic change over time. Additional time spent at home is 73% higher the average American. This may be attributable to additional use of ICT. Second, for population aged 65 and above the time use pattern has reversed. Time spent at the residence has decreased, while time spent in non-residence and transportation rose. This can be explained by another societal trend: an aging society. An aging society implies two relevant trends: an increased share of retired people in the population and an increased retirement age. Given a higher share of people greater than age 65 are participating in the workforce, this age group spends more time at work and correspondingly less at home compared to previous years.

2.3.3 **Lifestyle effect on energy demand across sectors.**

I next model shifts in energy consumption due to time-use changes using decomposition analysis. Details are discussed in the method section, but to briefly summarize, decomposition analysis distributes a change in energy use to a number of explanatory factors, such as population, house size, and efficiency. I use national aggregate data for annual energy use in residential, transport and non-residential sectors from 2003-2012 (EIA 2015b; BTS 2016). The non-residential sector is from the Commercial Building Energy Consumption Survey (CBECS) and includes offices, retail stores, warehouses, restaurants, and public buildings such as schools (EIA 2016). The decomposition analysis allocates changes in energy use in each sector to a number of factors. For the residential sector, the explanatory factors are population, house-size, intensity and time. For the non-residential sector, the explanatory factors are population, building area, intensity (inverse of efficiency) and time. For the transport sector, explanatory factors are population, intensity (inverse of efficiency) and time-use. National data sources are used for population and building area, time use factors comes from results in Figure 2. The intensity effect is calculated as from the remainder after the other factors are estimated and can be interpreted as energy efficiency. In order to explore how accounting for time-use changes results, the analysis was done including and not including it as decomposition variable. Fig. 3 shows the decomposition of the change in energy use in all the three sectors over the years 2003 to 2012.
Energy consumption in the residential sector decreased by 1,160 trillion BTU over 2003 to 2012. Increases in population and house size over the years contributes to an increase in energy consumption by 2,400 trillion BTU. However, the intensity (or efficiency) effect has decreased dramatically, overcompensating the increase from population and household effects. The increase in time spent at residence by 19 hours per year translates to increase in energy consumption of 476 trillion BTU. The total change in energy use in the non-residential sector is very small. In traditional decomposition analysis, this is explained by increases in population and building area balancing improved efficiency. Unlike the residential sector, the area effect is larger than the population effect. Accounting for time-use, results show what time spent in non-residential buildings decreases by 16 minutes per year, translating to a decrease in energy
consumption. The energy consumption in the transportation sector decreased by 1,600 trillion BTU. Higher population drove increases, more than compensated for by improved efficiency and decreased use of vehicles. Note that accounting for time effect affected the portion of energy change to intensity (or efficiency). This is relevant to future decomposition analyses of national energy trends.

Fig. 4 summarizes the energy impact of respective sectors due to time use changes. The main result from the decomposition is that from 2003 to 2012 the energy change due to time effect is a net decrease of 1,700 trillion BTU, which corresponds to 1.8% of primary energy use in the United States in 2012. Presuming the bulk of time-use induced change has been capture, this suggests that shifts in what and where Americans are doing is a significant factor in determining energy demand.

The interpretation of net energy reduction of staying at home is that addition residential energy is more than compensated for by reductions in transportation and non-commercial building. The reduction in transportation energy can be interpreted directly in terms of reduced VMT. The interpretation for non-commercial buildings is complicated by different building types being aggregated into one sector. To conjecture using building area statistics, note that per capita retail space reduced by 6.5% from 2003-2012, while per capita warehouse space increased by 20%. Per capita office space increased by 21%. The reduced energy use in non-residential is thus plausibly due to lower energy consumption in warehouses versus retail spaces and home offices saving energy over office buildings. Verifying this conjecture is a challenge for future models, part of the larger issues of model caveats discussed next.
2.3.4 Caveats.

A full accounting of energy changes induced by lifestyle changes is beyond the scope of the model. The current decomposition analysis framework captures only the aggregate effect of the sectors defined as measured through time spent in these sectors. There are additional connections between sectors not expressed by time use. For example, additional use of the Internet at home induces the manufacture and operation of servers and networks. The purchase of goods is a part lifestyle important for energy, inducing additional demand within and outside the U.S. While one can imagine a future disaggregated model that captures such additional factors, I argue that I have captured first order effects based on the following arguments.

Direct energy consumption in residential, transportation and commercial sectors account for 81% of primary energy consumption in the U.S. For transportation, energy and time-use, e.g. driving, correlate closely. While there is a part of energy use in the residential sector insensitive to time spent at time, electronics, lighting and some portion of heating and cooling energy use should scale. The commercial sector is diverse and has more complicated connections with lifestyles, but time spent in offices and retail stores should reasonably connect to energy use.

Scoping the scale of the energy use of networks, estimates put the U.S. energy consumption of servers at 40 TWh in 2003 and 65 TWh in 2012 (Shehabi et al. 2016). This corresponds to 410 and 665 trillion BTU respectively. The growth in server energy use is thus 15% of the 1,700 trillion BTU of the time-use induced energy change from Figure 2-5. It is thus expected that
inclusion of network operation induced by consumers would add to, but not dominate, energy changes induced by ICT lifestyles.

2.4 Discussion

Our fundamental point is that shifts in lifestyle induce interdependent changes in the energy consumption in multiple sectors. Because lifestyle choices ultimately lead to decisions on allocating time in a fixed 24-hour day, any change in one direction necessarily induces changes elsewhere. The apprehension of trends in energy demand should endeavor to capture interactions between lifestyle changes and use of energy technologies. Our results show non-trivial differences in shifts in energy use when including time-use, it can thus play an important role in future models. Especially with the advent of autonomous vehicles and increased access for shared mode of travel activity, time use patterns can be expected to shift profoundly. A time use based analysis would improve forecasts of energy demand.

What do our results imply for energy policy? One issue is shifting priorities for energy efficiency policies. The EPA Café standards for automobile efficiency is arguably the centerpiece of efficiency improvement efforts by the federal government. If however, trends towards decreased vehicle continue, compounded by car sharing, the effect of improved vehicle efficiency goes down. While spending time at home is, per minute, much less energy intensive than driving, people use an increasing portfolio of energy consuming ICT devices to enhance their time at home (Ryen, Babbitt, and Williams 2015). Given these trends, additional emphasis on improving efficiency of consumer electronics and home appliances might be warranted.

A second potential policy implication is the role time use could play in personalized plans for energy efficiency. Home energy audits, for example, account for a particular home’s major appliances such as furnace or insulation, but do not consider how the residents’ lifestyle choices affect energy use and the effectiveness of different technology interventions. I have shown in prior work that at least for televisions, heterogeneity in time use leads to large heterogeneity in energy consumption (Sekar, Williams, and Chen 2016). Accounting for behavioral
heterogeneities, including time use, has potential to reveal a different set of benefit-cost profiles for energy interventions.

What are the gaps in measuring time use for energy management purposes and how might they be addressed? The results suggest that two megatrends, digital and aging society, play major roles in activity shifts. While the ATUS includes some questions on ICT-related activities, detailed information may not available. For example, ATUS does not classify various activities performed when using computer for leisure. Further, ATUS does not record secondary activities i.e., a person cooking and watching television reports only one activity during the survey. Therefore, future ATUS could include time use categories that provide improved information on ICT related activities. The importance of the digital society for economic and social issues provides additional motivation for an increased focus on ICT-related activities. While surveys are the traditional tool to measure time-use, ICTs present an opportunity for personalized and real-time measurement. While adoption to date has emphasized personal health applications (e.g. FitBit), there are many untapped opportunities in the energy domain.
Chapter 3: Effect of consumer heterogeneity on residential rebate programs in the U.S.

Chapter Summary
Information provided to consumers and energy efficiency rebate programs generally assume characteristics of an average consumer. There is, however, substantial heterogeneity in behavior, energy prices and impacts of electricity use. To understand the impact of heterogeneity on rebate programs, the economic and carbon benefits of efficient choices of three household technologies (television, clothes washer and dryer) are assessed for different locations and usage patterns. For some households, an efficient energy washers and dryers do not save money, but brings substantial economic benefits to others. Viewing utility appliance rebate programs as tools for carbon abatement, abatement cost of carbon was assessed. At current rebate levels, for an average household, the abatement cost for carbon exceeds social cost of carbon (SCC). However, subpopulations with abatement cost less than SCC exists: 4%, 6%, and 41% for televisions, washers and dryers respectively. Therefore, abatement programs can benefit from targeted intervention.
3.1 Introduction

Heterogeneity in consumer behavior, energy prices and impacts from the energy consumption, are important variables when designing incentive policies for adoption of efficient and/or advanced technology. Consumers facing higher energy prices and energy usage are more economically motivated to adopt the technology compared to their counterparts. In terms of carbon mitigation, participation from consumers living in a carbon intensive grid is more important than consumers from cleaner grids. Since most energy policies have multiple goals, decision makers have a hard task of designing policies that balance between carbon mitigation goals, energy savings and adoption targets. However, many federal and local incentive programs in the past and current provide constant rebates that do not vary with consumer heterogeneity. Examples include, incentives for electric vehicles, residential solar PV and utility energy efficiency programs.

Researchers have not only shown that heterogeneity is important but also that blanket programs are inefficient by design (Allcott et al. 2015). Cai et al. (2013) and Diamond (2009) studied the effects of prices and energy use heterogeneities on adoption of hybrid electric vehicles and residential solar photovoltaics (PV) respectively. They noted that adoption rates are larger among consumers experiencing higher fuel price and energy use. Whereas numerous studies analyzing heterogeneity in emission intensity, recommend geographically varied policies for cost effective abatement of environmental externalities including carbon (Holland et al. 2015; Michalek et al. 2011; Sekar et al. 2014; Siler-Evans et al. 2013). Further, (Holland et al. 2015) showed that the federal subsidy of $7500 for electric vehicles could be a net welfare loss to the society.

Therefore, policy planning tools such as the marginal abatement cost curves, energy efficiency supply curves can benefit from resolving for consumer heterogeneity. The famous McKinsey cost curves for carbon abatement and energy efficiency supply ignore both geographic and consumer heterogeneity(Nauclér and Enkvist 2009; Bouton et al. 2010; Granade et al. 2009). Recently however, studies have resolved for some uncertainties in the model. To account for heterogeneity in the energy and water prices, (Chini et al. 2016) developed separate abatement
cost curves of electricity and water from energy efficiency measures for selected cities in the U.S., however behavior heterogeneity has largely been neglected in the literature.

This paper focuses on residential energy efficiency programs. Residential energy efficiency programs offer incentives to purchase high energy efficient products to realize multiple goals including energy, non-energy savings and market transformations. Currently, utilities all over the U.S. have consumer funded energy efficiency programs with a total spending of more than $1.7 billion dollars in the year 2015 and the total budget is expected to increase over the years (Barbose 2014; CEE 2015). Residential programs include a variety of measures to save energy including appliance recycling, behavior feedback, consumer rebates for products, financing, whole home audits, retrofits and many more.

Given the large scale of operation, utility commission and energy efficiency program administrators have established practices for planning and evaluating the cost effectiveness of the efficiency programs. Recent research has shown that the average levelized cost of electricity saved from the residential energy efficiency programs are around 0.033$/kWh (Hoffman et al. 2017), close to that of whole sale electricity prices. Therefore, energy efficiency programs are considered the most cost-effective method for savings electricity.

However, energy efficiency programs, specifically the appliance rebate programs, do not consider consumer heterogeneity in their program development and evaluation. Expected savings from energy efficiency measures are calculated based on average consumer. Typically, a deemed savings calculation that assumes average behavior of the appliance across the population is used. For example, the energy savings from clothes washer is calculated based on the assumption that the number of loads is 295 per year for all participants (State and Local Energy Efficiency Action Network 2012; Illinois Energy Efficiency SAG 2017).

In the U.S., consumer heterogeneity at the households can be large. The number of clothes washer loads can vary from 50 to 780 per year. Energy consumption among single family household in the years 2009 varied between 1 and 524 BTU/sq.ft (EIA 2012). In addition, there is significant heterogeneity in electricity prices and emissions intensity of the grid. The average
residential retail electricity price across the states varied between 9 and 29 cents/kWh in the year 2015. Carbon emissions factor of electricity varied between 23 and 2084 (lbs./MWh) across the states in 2013 (USEPA 2017). Regional variation in prices and emissions factors may not impact region specific utility programs however it is important for national level policy planning.

Further, participation rate in energy efficiency programs are low. In the case of State Energy-Efficient Appliance Rebate Program (SEEARP), which provided around $300 million for residential appliance as rebates over three years between 2009 and 2012. 33% of the total rebate value was given for energy efficient clothes washers. A back of the envelope calculation shows that only 1.4% of eligible households participated in the program. Any single-family homeowners with clothes washer greater close to end of life 9 years or older was assumed to be eligible since most program administrators limited SEEARP rebate to single-family homeowners. According to RECS around 60% of the single-family dwellings had washers greater than 9 years old.

Due to the average behavioral assumption and lower participation rates the probability of the actual savings realized being equal to expected savings claimed is low. In such cases rebate programs would are considered inefficient.

The objective of the paper is to understand the combined effect of behavior heterogeneity and geographic heterogeneity i.e., fuel prices and emission factors on energy efficiency programs. Since energy efficiency programs include large portfolio of multiple measures, the paper focuses on rebates for selected consumer products including Clothes washers, Clothes dryers and Televisions. Specifically, the monetary and environmental benefit for the consumers and the utility from purchasing a standard Energy Star certified versus a baseline version of clothes washers and dryers, and television is calculated. Although the scope of the project may look small but it is significant for three reasons. Firstly, these three products contribute to approximately 14% of all the total energy consumed at U.S. households. For a typical home in the year 2014, the average energy consumption of clothes washer and dryers and Televisions were 3%, 5% and 6% respectively. For clothes washer, it is assumed that 80% of energy is required for water heating. Secondly, the three products have a significant behavioral
heterogeneity. Finally, there are around a total of 175 programs around the country offering rebates for TV, washer and dryer combined.

Publicly available data such as American Time Use Survey (ATUS)(BLS 2015b) and Residential Energy Consumption Survey (RECS)(EIA 2012) provide the user behavior, geographic information and demographic information for the three products. State level energy prices and emission factors are obtained from EIA databases. Energy, carbon savings and price difference from purchasing an Energy star equipment are obtained from respective Energy Star technical documentation. This paper would be the first empirical analysis of the effect of behavioral and geographic heterogeneity in rebate programs of the selected appliances. It also emphasizes to the utility program managers and evaluators the importance of accounting consumer heterogeneity when implementing and evaluating the utility energy efficiency programs. Finally assessing heterogeneity will help in designing more realistic and useful policy tools such as the abatement curves.

3.2 Methods and Data
To understand the impact of behavioral and geographic heterogeneity in the adoption of energy star certified televisions, clothes washer and dryer, the variability in energy savings, economic benefit and carbon savings for various households are calculated. To assess the cost-effectiveness of the rebate program abatement cost of electricity and carbon are calculated and compared with respective benchmarks, cost of electricity production and social cost of carbon. The effects of behavioral and geography heterogeneity are also studied in isolation from each other to gauge their influence on the distribution of the various metrics measured. Finally, demographics of high energy and carbon use are determined.

3.2.1 Specification of the Energy Star Products
The effects of consumer heterogeneity are tested for savings obtained from a standard energy star product versus a baseline available in the market. The specifications for the Energy Star and the baseline version such as energy savings, water savings and incremental price are obtained from the Energy Star technical reference manual and personal communications. Table 1 shows the various assumptions for the three products considered.
The specifications for clothes washer vary depending on their technology type and size. Front loading washers are more energy and water efficient than the top loading type however front-loading washers cost more. An energy star cloth washer would save both energy and water. Washers energy and water consumption are measured identified by their rated unit electric consumption and integrated water factor (IWF) respectively. IWF is the ratio of the weighted average water consumption for wash cycles divided by the capacity of the washer expressed as gallons/ft\(^3\). For this paper, energy savings and water savings from a 4.5 ft\(^3\) energy star washer is compared to federal standards using their respective factors. It must be noted that 80% of the energy is assumed to be used for heating the water while 20% as machine energy. Gas to electricity factor of 75% is assumed when the source of heat is gas. The incremental cost of Energy Star washers is $190 and $50 for top loading and front loading respectively.

Clothes dryer calculations are similar to that of the washers. The energy factor of clothes washers is indicated by combined energy factor (CEF) which is the ratio of the load size and the energy use during operation. The load size of 8.45 lbs. per wash is assumed. The CEF for dryers of capacity 4.4 ft\(^3\). or more are used for energy savings calculations. The incremental cost of sales weighted energy star versus nonstandard versions was $75.

In the case of Televisions, the sales weighted average Energy Star device consumes 81 kWh/year while non-energy star product consumes 112 kWh/year. The size segment of the representative TV would be 50” LCD. Energy Star assumes an average TV usage of 5 hours per day to calculate the total energy consumption estimates. According to Energy Star and Itron (Itron, Inc. 2014) there is no statistically significant difference between the prices of Energy Star and non-Energy Star devices. Based on the energy consumption and average usage rates, the power difference was identified to be 17W during operation. The power difference between energy star and baseline product during standby mode is considered insignificant since the power draw during standby mode was already less than 1W for all devices. The energy savings are calculated as the product of power and hours of television usage.
Energy Star summarizes all the rebates available across the country. There were only 4 programs identified for TV with rebates varying from $25 to $150. While for clothes washer there are 105 programs with rebates varying between $20 and $235 while for clothes dryer there are 65 programs with rebates varying between $25 and $300. A typical rebate for clothes washer and dryer are around $50. A sample calculation of the energy and water savings for each device is shown in the supporting information.

Table 3-1 List of assumptions used to calculate the savings and other metrics from Energy Star (ES) technologies along with their sources. Sources: Television behavioral use: ATUS, Washer and Dryer use characteristics – RECS, and all other data are obtained from Energy Star.

<table>
<thead>
<tr>
<th>End Use Technology</th>
<th>Behavior</th>
<th>Characteristics</th>
<th>Incremental Cost</th>
<th>Rebates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Television</td>
<td>Time spent (hours/year)</td>
<td>50” LCD, 7 Years lifetime</td>
<td>$0</td>
<td>4 programs $25 - $150</td>
</tr>
<tr>
<td>Clothes Washer</td>
<td>No. of loads/year</td>
<td>4.5 ft³, Top Loading, 11 years lifetime</td>
<td>$190</td>
<td>105 programs $20 - $235</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4.5 ft³, Front Loading, 11 years, 392 loads/year</td>
<td>$50</td>
<td></td>
</tr>
<tr>
<td>Clothes Dryer</td>
<td>No. of loads/year</td>
<td>5 ft³, Electric Heater, 12 years, 8.5 pounds per load</td>
<td>$75</td>
<td>65 programs $25 - $300</td>
</tr>
</tbody>
</table>

3.3 Microdata on consumer behavior, fuel prices and carbon emission factors

The microdata for behavior and geographic heterogeneity are obtained from two public national level surveys the American time use survey (ATUS) and the Residential energy consumption survey (RECS). ATUS provides information on television watching in hours per day and RECS informs number of washing and drying loads and the type of fuel used at the household. Along with the behavioral information both the datasets provide demographic information of the participants that includes their state or state group. Using the geographic data, fuel prices and carbon emission factor are identified for each respondent. The EIA provides information on the
fuel prices by state. While emission factors of the grid resolved by states are obtained from eGRID (USEPA 2017).

ATUS is an annual survey conducted by the Bureau of Labor Statistics (BLS) since 2003. Respondents for the survey are 15 years and older. Annual participation in the survey exceeds 11,000 respondents each year. Only one household member is sampled per household. The survey is conducted using computer-assisted telephone interviewing (CATI) in which the participants respond on how they spent their time on the previous day, the location of their activity, and information about people they were with when performing the activity. Conducting the survey via a conversational interviewing style mediated by an expert is assumed to improve reporting accuracy. In addition to the activity information, ATUS also collects respondent's household level socio-economic data such as age, income, sex, race, marital status, education level, employment status and many others. The ATUS website provides more information about the survey (BLS 2015b).

RECS is conducted once every several years by the energy information agency (EIA). The latest RECS was conducted for the year 2009. The objective of the survey is to characterize the energy consumption of households by collecting household behavior and the physical characteristics of all the end use technologies such as age, technology type, type of fuel and information about the building. The geographical characteristics of RECS is limited to state groups. The state groups seem to be formed under the discretion of the EIA. More information on the RECS can be found elsewhere.

The emissions and generation resource integrated database (eGRID) provides emissions data for electricity power sector. It first collects plan-specific data for all U.S. electricity generation plants and summarize various emissions statistics including carbon emissions factor aggregated at various levels include plant, state, and grid regions). The emissions are allocated to the plant that produced the electricity therefore aggregate emission factor data does not consider any electricity trade. Despite this shortcoming, eGRID is the best proxy for state-level emission factors available. The latest data for emission factors are available for the year 2014.
3.4 Behavioral heterogeneity in TV, Clothes washers and dryers.

Figure 1 shows the heterogeneity in television watching patterns and frequency of washing and drying loads in the U.S. The data for television represents the year 2015 usage patterns for each person in the U.S. Washer and dryer load represent households in the U.S for the year 2009. At the time of writing new RECS data was unavailable therefore 2009 usage data is assumed to hold true for the analysis.

Around 22% of the population in the U.S. reported not watching televisions. The average television watching time in the U.S. is 2.5 hours per day. When not including the population that do not watch TV the average watching time increases to 3.25 hours per day. There is large variability in the TV watching time with more than 20% of TV watchers spending more than 5 hours per day.

The washer and dryer data does not include households living in apartment buildings or using common/public washer and dryers. Around 18% and 20% of the households reported they do not use clothes washer and dryer in home respectively. Most households use between 2 to 4 loads per week. And 80% of the people use the dryer as frequently as the washer. Variability in washer and dryer use is also large as frequency of loads per week can vary by an order of magnitude (1 loads per week to more than 15 loads per week). Unlike the data on television usage, frequency of washers and dryers are available as binned data therefore I used mean values of the bins. For the extremes estimates, less than or equal to 1 and 15 or more loads per week a value of 1 and 15 were assumed. The uncertainty arising from this assumption would be discussed later in the paper.

RECS also provide the technology type, 81% of the households have top loading washer. And 50% of the household use electricity for heating around another 47% used natural gas. And 80% of the household have electric dryer.
3.5 Geographical heterogeneity in energy prices and emission factor

The products considered here use electricity and natural gas as fuel and save electricity, natural gas and water. Table 2 summarizes the heterogeneity of prices and emission factors. The median electricity price, natural gas price and electricity emission factor are 12.13 cents/kWh, $1.1/therm and 1128 lbs/MWh respectively. The variability of electricity prices, and emission factor are not as large when compared to the behavior. The minimum and maximum of the electricity prices, and their emissions factors are 0.8, 1.63 and 0.39, 1.6 times the median respectively. The min and max for natural gas prices are 0.72 and 1.7 times the median. The emission factor for natural gas is constant at 5306 g/therms. Efficiency clothes washer gain significant water savings than their baseline therefore adding the economic benefit from water savings is important however, location specific water prices are not available therefore a constant value of $10.53 per 1000gallons including sewer rates is assumed.

Table 3-2 Variability in prices of electricity, natural gas and water and emission factor in the U.S. State specific data is available in the supporting information.

<table>
<thead>
<tr>
<th>Item</th>
<th>Units</th>
<th>Min</th>
<th>Median</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015 Electricity Price</td>
<td>cents/kWh</td>
<td>9.76</td>
<td>12.13</td>
<td>19.83</td>
</tr>
<tr>
<td>2015 Natural gas Price</td>
<td>$/therm</td>
<td>0.79</td>
<td>1.1</td>
<td>1.95</td>
</tr>
<tr>
<td>Water Price</td>
<td>$/1000</td>
<td></td>
<td>10.53</td>
<td></td>
</tr>
</tbody>
</table>
### 3.5.1 Formulation of the metrics

Various metrics are proposed to measure effect of heterogeneity including energy savings, net present value, carbon abated and abatement costs. Net present value is the sum of the incremental cost and discounted monetary benefit from purchasing the Energy Star technology. Television and clothes dryer only have energy savings while washers save energy and water. Equation 1 expresses NPV in mathematical form.

\[
NPV_{T,i} = -IC_T + \sum_{y=1}^{n_T} \frac{eS_{T,i} * eP_i + ngS_{T,i} * ngP_i + wS_{T,i} * wP}{(1 + r)^y}
\]  

(1)

Where, \(NPV_{T,i}\) is Net Present Value from purchasing end use technology \(T\) for each person or household \(i\). \(eS_{T,i}, ngS_{T,i}, wS_{T,i}\) are electricity, heat and water savings from technology \(T\) for each person or household \(i\) respectively. The energy savings and water savings are calculated based on the formula shown in supporting information. It is assumed that households do not switch technology type. A household with front loading washer continues to choose the same technology type. \(eP_T, ngP_T, wP\) is electricity prices for each person \(i\) respectively. \(r\) is discount rate at 5% and \(y\) is the lifetime of end use technology \(T\).

Carbon abated is calculated based on carbon emission factors of the fuel saved. In the case of households with natural gas water heaters emission factors of electricity and natural gas are used. 3% of households use propane and heating oil as fuel for heating water, for those cases natural gas emission factor and prices are used. Further, variability of carbon emission factor of heating oil and propane are 18% and 36% higher than natural gas emission factor.
Tons of Carbon abated (in tC)

\[ t_{C,i} = eS_{T,i} * eEF_i + n gS_{T,i} * n gEF_i \]  

(2)

Where, \( eEF \) and \( n gEF \) are the emission factors for electricity and natural gas for each person or household \( i \). \( t_{C} \) is the tonnes of carbon dioxide abated from each technology for each person or household \( i \).

Abatement cost of carbon is the ratio of cost of adopting a technology and the amount of carbon saved. Abatement cost of carbon is calculated both for the consumers and the utilities. In the case of consumer cost of adopting the technology is equal to negative of the net present value calculated above. In the case of utilities, the cost of technology is the value of the rebate and overhead expenses. For simplicity, I do not include the overhead costs. Since rebates are also used to save energy, abatement cost of electricity is also measured as the ratio of rebate and total electricity saved.

Consumer Abatement cost of carbon (in $/tC)

\[ CACC_{T,i} = \frac{-NPV_{T,i}}{t_{C,i}} \]  

(3)

Utility Abatement Cost of carbon (in $/tC)

\[ UACC_{T,i} = \frac{rebate_T}{t_{C,i}} \]  

(4)

Utility abatement cost of electricity (in $/kWh)

\[ UACE_{T,i} = \frac{rebate_T}{eS_{T,i}} \]  

(5)

Where, \( rebate_T \) is the rebate amount in $ for each technology \( T \), and it does not vary with consumers.

### 3.6 Results and Discussion

Based on the methods described above, four results are presented and discussed in this section. First, the variability in metrics that focus on the consumers such as energy and carbon savings, NPV and consumer abatement cost are presented. Second, utility abatement cost for energy and
carbon are shown. In addition, percentage of population that are with abatement costs for carbon and electricity less than social cost of carbon and electricity price are discussed. Thirdly, interested sub populations are identified and their demographics are characterized. Finally, the isolated effects of behavior and geographic heterogeneity are discussed by comparing with the effect of total heterogeneity.

The mean energy and carbon savings are largest for dryers while washers have the highest monetary value due to both energy and water savings. As expected, energy and carbon savings and net present value varied linearly (positive slope) with behavior. In addition to behavior, carbon savings and NPV depended on geography. Places with higher energy prices and emission factors had larger net present value and emissions savings respectively. Surprisingly, for a small subset of the population the energy efficiency measures did not provide a monetary benefit (negative NPV) therefore had positive abatement cost of carbon many orders larger than the social cost of carbon (“Technical Support Document : Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866” 2013).

3.6.1 Heterogeneity in Energy savings and economics

Figure 3-2. shows the heterogeneity in energy savings and the net present value of the purchasing an energy efficient technology. Large heterogeneity is observed across all the metrics measured.

3.6.1.1 Clothes Washers

The weighted average energy savings from households buying clothes washers was 95kWh/year corresponding to an average behavior of 5.6 loads per week and a minimum and maximum energy savings of 5.5 and 200 kWh/year for households with lowest and highest behavioral characteristics. Since technology/fuel switching is not included, no difference in energy savings between households with gas or electric is observed. Average water savings is 4500 gallons per year, with a minimum and a maximum of 234 and 14391 gallons per year. The net present value of clothes washers varies between -$9.1 to $140 with mean of $28 per year. 8% of the residents have the negative NPV while 7% have NPV greater than $90 per year ($1000 over lifetime and approximately $700 higher than an average consumer). Note Energy Star reports an average savings of $45 per year. For washers, water savings provide additional value to the consumers
compared to dryers and TV. When not including the incremental cost, the water savings provide 70 to 90% of the monetary benefit. The water price is assumed constant and it includes sewer price. Typically, sewer prices are 3 to 5 times higher than water consumption rates.

3.6.1.2 Clothes Dryer

Dryers have the maximum energy savings of the three technologies evaluated here. Mean energy savings is approximately one order higher than televisions and twice that of washers. In this work, only electric dryers are considered and their behavior is assumed to be similar as washers. Therefore, variability in the metrics are large. Mean energy savings from dryers is 167kWh/year with a minimum and maximum of 30 and 445kWh/year. Life time of dryer is 12 years, longer than TV (by 5 years) and washers (1 year), therefore total energy savings over lifetime are larger. The net present value of dryers varies between -$4.1 and $59 per year. Despite their larger energy savings and longer expected lifetime the total monetary benefit from dryers are lesser than washers. Around 7.5% of the residents do not recover their cost of investment and 20% save double the average savings.

Figure 3-2 Energy Savings and Net present value of television, clothes washer and dryer. The red dotted line indicates the mean.
3.6.1.3 Televisions

Large variation in behavior for televisions were observed with min and max of 0.02 and 23.8 hours per day of television watching. Since the extreme values cannot be compared to actual behavior therefore 10th and top 90th percentile values are reported. In the case of TV viewing hours per day the 10th and 90th percentile values are 0.8 hours and 7 hours respectively. Energy, and monetary benefit of televisions are the lowest compared to other efficiency measures.

3.6.2 Heterogeneity in carbon abatement and consumer abatement cost

3.6.2.1 Clothes washer:

Due to the energy savings, the total carbon abated over the life time of the technology (11 years) varies between 0.01 to 2.7 tons of carbon. The range of carbon savings are larger than energy savings because of the additional heterogeneity due to geography (emission factors). Consumers with negative NPV have a positive carbon abatement cost, since total carbon savings are less than 1 ton per consumer, their carbon abatement costs are significantly high ranging between 500 to 1770 $/tC. Embedded carbon emissions from water savings are not considered in this paper, therefore the carbon abatement costs have larger magnitude in both the directions.

Although it is widely assumed that natural gas is less carbon intensive than electricity, it is interesting to note that certain locations save more carbon when using electricity instead of gas for water heating. Two effects are in play: first, the carbon intensity of electricity in states are lower. Idaho, Maine, New Hampshire, Oregon, Vermont, Washington have electricity carbon intensity less than 400 lbs/MWh equivalent to natural gas carbon emission factor of 5302g/therm. Second, total energy consumption of washers with gas heated water are higher than their counterpart since efficiency of gas heater are 0.75 times that of electric heaters.

Caveats: In this paper, technology switching is not considered. For example, households with front loading type clothes washer is assumed to buy the same technology. Improvement in energy and water efficiency of Energy star certified top loading washers compared to their baseline is larger than front loading clothes washers. For example, for a household with behavior of 3 wash loads per week, if they already own a top load type washer, their energy and water savings would be approximately 3 times and 4 times higher than the case when they own a front
load type washer. Since front loading clothes washer typically consumer less energy and water, moving from front to top will have larger savings, while the vice versa has the opposite effect respectively. Similar scenario exists in the case of carbon savings when switching from electricity to heat for heating water and dryer technology.

3.6.2.2 Clothes Dryer:
Carbon savings track with energy savings, dryers saves two times more carbon than washers and television combined assuming an average consumer. Due to large carbon benefit and smaller monetary benefit the large values of carbon abatement cost as seen for washers was not observed.

3.6.2.3 Television:
Carbon abated tracks with energy savings and as expected is the lowest compared to other efficiency measures. Further, due to zero incremental cost for energy star TVs carbon abatement cost are always less than zero. However, the variability of the various metrics is large since they track with variability in behavior.

Figure 3-3 Carbon abated, and Marginal abatement cost of television, clothes washer and dryer. The red dotted line indicates the mean.
3.6.3 Cost-effectiveness of rebates

Despite the large monetary benefits from purchasing an Energy Star product, the rate of adoption is small due to various issues such as, information asymmetry, inattention to energy costs, credit constrains and etc. (Allcott and Greenstone 2012; Gillingham and Palmer 2014; Palmer et al. 2013). Therefore, incentives are used as a mechanism to encourage adoption. In average, rebates are not cost effective for televisions and washers since mean abatement cost of carbon and electricity are higher than social carbon cost of $48/tC and electricity prices of $0.126/kWh or levelized cost electricity (LCOE) production from a new natural gas power plant at $.07/kWh. Washers breakeven when compared with wholesale electricity prices at average of 0.035$/kWh. Figure 3-4 shows the abatement cost of carbon and electricity measured as $/tC and $/kWh. Since the objective is to calculate the value of the rebates, consumer costs are not included. Typical rebates assumed for televisions, washers and dryers are $10, $50 and $50 per each product purchased respectively. To understand the total/social abatement cost of carbon the consumer and utilities abatement cost are to be summed.

Since the rebates are assumed constant, abatement costs of carbon and electricity depends only on carbon and electricity savings respectively. Carbon and electricity savings are large for dryers and therefore they have a higher cost-effectiveness. The variability in the utility abatement cost follows the variability in carbon and electricity savings. The magnitude of the savings for carbon are larger due to effect of both behavior and geography (emission factor), in the case of electricity savings, variability is due to only behavior, but still large.
In addition to the variability in abatement costs the percentage of population/households that are cost-effective for various rebates are shown in Figure 3-5. The definition for cost-effectiveness is described in the paragraph two above from here. Figure 3-5 shows that as the rebates increases, the percentage of population that are cost-effective decreases rapidly at the beginning and at a slower pace near the end. Usually program administrators have an overhead of about 25% which worsens the cost-effectiveness.

At typical rebate rates, less than 4%, 6% and 41% of the population are cost effective for abatement cost of carbon, and about 60%, 45% and 90% are save electricity at less than average electricity price of 12.65 cents/kWh. When comparing abatement costs with whole sale electricity prices the percentage of population is expected to decrease.
3.6.4 *Which heterogeneity is important, behavior or geographic (energy prices and emission intensity)?*

Behavioral heterogeneity among the products is more important than the geographic heterogeneity i.e., energy prices and carbon emission intensity of electricity. Figure 3-6 shows the effects of individual heterogeneity on NPV and carbon abated. NPV is a function of behavior and electricity prices while carbon abated is a function of behavior and carbon intensity of electricity. Variability is shown using a density plot that assumes a Gaussian distribution with parameters determined through kernel density estimation algorithm referenced elsewhere. Density plot is particularly useful for presentation purposes.

The density for all the products clearly show that behavioral variability closely follows the density of the case that combines all heterogeneities. Since the behavior data is smooth for televisions, the distribution is simple with a single peak. In the case of washer and dryer, behavior is represented as discontinuous but numeric values therefore many peaks are observed.
For all the cases shown in the Figure 3-6, the distribution of the behavior heterogeneity case i.e., average fuel prices and emissions is closely associated with the distribution that combines both scenarios. The importance can be seen from the standard deviation estimates of the behavior, energy prices and emission intensity estimates. Coefficient of variation or SD divided by mean estimates for television, wash loads are 0.8 and 0.63 respectively. The values are higher than emission prices and emission intensity at 0.28 and 0.45 respectively.

Figure 3-6 The effect of behavior and geographic heterogeneity in isolation on NPV (below) and carbon abated (above) compared to scenario when both heterogeneity are included.
3.6.4.1 Demographics

The objective of determining the demographics of the subpopulation is to identify those households with largest benefits or least benefits. From the results discussed above the following subpopulations are of interest. 1) households with negative NPV and consequently positive consumer abatement cost of carbon and 2) households that double the average energy savings. Based on the discussion of the importance of heterogeneity, behavior is expected to primarily differentiate the subpopulations.

All households with wash load frequency 1 or lesser have negative NPV for washer and dryer. Most of household members live alone or live with their partner. There is no clear demarcation of the income distribution between households with 1 or lesser wash loads and others. About 45% of the household earn less than $30k while 16% earn more than 75K. Age explains income distribution and the household members. For households earning less than $30,000 their median age of the household is 67 and more than 70% live alone while others live with their partners. When earning more than $30,000 median age is 57, typically employed and more than 40% living with others (more than one household member). The same is true for the demographics of households that would have a negative NPV for dryers.

Households that double the energy savings compared to the average consumer watches television for more than 6.6 hours and has wash load frequency of more 10 or more. In the case of television, the demographic of high energy savings would be people who are older, less educated, without employment and earns less money compared to their counterparts. In other words, consumers to target for televisions are to be avoided for washer and dryer. The high-energy savings consumers for washer and dryer (>10 loads per week) have an average of more than 4 members at the household with atleast 2 children. More than 45% of the households in this group earn more than $75,000 per year (100% employed).

3.6.5 Uncertainties

Since the objective of the paper is to measure the variability and its effect on rebate programs, accurate information on behavior is helpful. Current data for behavior from RECS are universally used by both industry and researchers. However, assumptions such as: 1) using bins
as discontinuous but numeric values based on their mean and 2) frequency of wash loads 1 or less and 15 or more were assumed to be 1 and 15 are not scientific. However, to my defense they continue to preserve the variability but slightly overestimate and underestimate the extreme cases thereby shrinking the distribution at the extremes. Therefore, households that have negative NPV are overestimated, i.e., NPV is expected to be more negative. Similarly, the energy savings from the high-energy consumption group is underestimated i.e., energy savings could be even more larger.

Other estimates in the models such as life of the technology, discount rate, difference between energy star and baseline energy savings rate are important in determining the correct savings estimate shifting the distribution to the right or left. Example a higher difference in energy consumption between the Energy Star and baseline would shift the distribution for energy savings to the right. At this point I do not conduct a sensitivity analysis although it does not qualitatively change the conclusions of this work.

3.7 Conclusion
Federal and local rebate programs do not include consumer behavior when planning energy efficiency programs. This chapter estimated the effect of behavior and geographic (electricity prices and carbon intensity of electricity) heterogeneity on various metrics such as monetary benefits, and abatement costs of carbon and electricity from buying an Energy Star certified television, clothes washer and dryer instead of a baseline technology. Large variability in various metrics are observed with 8% of the population not recovering their cost while approximately 12% and 20% save double the monetary savings compared to an average household from efficient washer and dryer respectively. When comparing the products against each other, clothes dryers have the least abatement cost with significantly larger population, 90% and 41%, savings electricity and carbon less than electricity prices and social carbon cost respectively. Further, effect of behavioral heterogeneity was found to be larger than variability in prices and emission factors on the metrics. Based on the results, it can be concluded that heterogeneity must be considered when evaluating energy efficiency programs.
The implications of these results are described with focus on two governing bodies that further the cause of energy efficiency: the administrators and evaluators of energy efficiency programs and Energy Star.

Given the large heterogeneity in consumer behavior a blanket marketing approach taken by rebate programs must be avoided. For many energy efficiency measures such as retrofit programs, the performance before and after the retrofit are measured on case basis. However, for rebate programs energy savings are based on deemed savings calculations. Since demographics can identify product behavior, administrators could collect demographic information of the participants to estimate energy savings and abatement costs. Since there is large amount of people with monetary benefits twice that of the average household, potential for free riding is large. Therefore, program managers must set appropriate rebates and explore targeted intervention to improve cost-effectiveness of the programs. Energy efficiency programs are a portfolio of various energy measures. If a portfolio of an imaginary utility includes only the three products studied here, the utility must focus on selling more dryers compared to televisions and washers because dryers have large energy and carbon savings and smaller abatement costs.

Energy Star website offer online calculators for quantifying the potential energy savings from their products compared to the market baseline. The online calculators solve for consumer heterogeneity by asking for the consumer specific information to come up with the savings. However, not all consumers use the online calculators before purchasing a product. For consumers that goes directly to the retailers, energy star labels provide a single number for monetary benefits. Example, $45/year from clothes washers assuming 295 loads per year. Consumers would benefit from an Energy Star label that could provide savings estimates depending on behavior.
### 3.8 Supporting Information:

Table S 3-1 State-wise data on carbon emission factor of the electric grid (USEPA 2017), electricity price and natural gas price (EIA 2015).

<table>
<thead>
<tr>
<th>State</th>
<th>2015 Retail Electricity Price (c/kWh)</th>
<th>2014 Grid emission factor (lbs/MWh)</th>
<th>Natural Gas Price ($/therm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AK</td>
<td>19.83</td>
<td>897.551</td>
<td>0.964</td>
</tr>
<tr>
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</tr>
<tr>
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</tr>
<tr>
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<td>1118.078</td>
<td>1.704</td>
</tr>
<tr>
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<td>16.99</td>
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</tr>
<tr>
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<td>1.955</td>
</tr>
<tr>
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<td>OR</td>
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<tr>
<td>WY</td>
<td>10.97</td>
<td>2022.767</td>
<td>0.933</td>
</tr>
</tbody>
</table>

Sample calculation of energy and water savings:

Clothes Washer:
Energy Savings is calculated based on rated unit electricity consumption. A baseline washing machine is assumed to meet the federal standards (DOE 2012). Energy consumption of a washing machine consists of two parts: the energy needed to heat the water and the machine energy. Depending on the household, water heating can be electricity or gas. Water savings is calculated based on integrated water factor (IWF).

Calculation of energy and water savings for a sample household follows. The household purchases a top-loading clothes washer and uses natural gas for water heating. In the sample calculation, the consumer behavior i.e., loads per year and type and size of the machine, before and after purchase remains the same.

\[
Electricity\ Savings = (RE_b - RE_{ES}) \times \frac{Load_{User}}{Load_{Ref}} \times (1 - P_h) = (381 - 230) \times \frac{295}{392} \times 20\% \\
= 22.7kWh/year
\]

\[
Heat\ Savings = (RE_b - RE_{ES}) \times \frac{Load_{User}}{Load_{Ref}} \times \frac{P_h}{\eta_{WH}} \times \theta = (381 - 230) \times \frac{295 \times 80\% \times 0.0341}{392 \times 75\%} \\
= 4.1\\text{therm}
\]

If the source of water heating is electric \(P_h\) becomes zero.

\[
Water\ Savings = (IWF_b - IWF_{ES}) \times C \times Load_{User} = (8.4 - 4.3) \times 4.5 \times 295 = 5442.7\\text{gallon}
\]
Table S 3-2 Parameters used to calculate energy and water savings from clothes washers. Parameters for front loading washers are also given but are not used for the sample calculation above.

<table>
<thead>
<tr>
<th>Item</th>
<th>Notation</th>
<th>Units</th>
<th>Top Loading</th>
<th>Front Loading</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline Rated unit electric consumption</td>
<td>$RE_b$</td>
<td>kWh/year</td>
<td>381</td>
<td>169</td>
</tr>
<tr>
<td>Energy Star Rated unit electric consumption</td>
<td>$RE_{ES}$</td>
<td>kWh/year</td>
<td>230</td>
<td>127</td>
</tr>
<tr>
<td>Baseline Integrated Water Factor</td>
<td>$IWF_b$</td>
<td>gallons/ft³</td>
<td>8.4</td>
<td>4.7</td>
</tr>
<tr>
<td>Energy Star Integrated Water Factor</td>
<td>$IWF_{ES}$</td>
<td>gallons/ft³</td>
<td>4.3</td>
<td>3.7</td>
</tr>
<tr>
<td>Reference Load</td>
<td>$Load_{Ref}$</td>
<td>Loads/year</td>
<td>392</td>
<td></td>
</tr>
<tr>
<td>User Load</td>
<td>$Load_{User}$</td>
<td>Loads/year</td>
<td>295</td>
<td></td>
</tr>
<tr>
<td>Capacity</td>
<td>C</td>
<td>ft³</td>
<td>4.5</td>
<td></td>
</tr>
<tr>
<td>Energy for Water heating</td>
<td></td>
<td></td>
<td></td>
<td>Natural Gas</td>
</tr>
<tr>
<td>Rated electricity used for water heating</td>
<td>$P_h$</td>
<td>%</td>
<td></td>
<td>80%</td>
</tr>
<tr>
<td>Gas water heater efficiency</td>
<td>$\eta_{WH}$</td>
<td>%</td>
<td></td>
<td>75%</td>
</tr>
<tr>
<td>Energy Conversion</td>
<td>$\theta$</td>
<td>therm/kWh</td>
<td></td>
<td>0.0341</td>
</tr>
</tbody>
</table>

**Clothes Dryer:**

Energy savings of clothes dryer is calculated based on combined energy factor. Energy savings for a sample household that purchases an efficiency electric dryer is shown below. Similar to the washer, consumer behavior is assumed not to change after the purchase of the dryer.
\[
\text{Electricity Savings} = \left( \frac{W_{\text{load}}}{CEF_b} - \frac{W_{\text{load}}}{CEF_{ES}} \right) \times \text{Load}_{\text{User}} = \left( \frac{8.5}{3.11} - \frac{8.5}{3.93} \right) \times 295
\]

\[= 168.2 \text{ kWh/year}\]

Table S 3-3 Parameters used to calculate energy for dryers.

<table>
<thead>
<tr>
<th>Item</th>
<th>Notation</th>
<th>Units</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline Combined Energy Factor</td>
<td>$CEF_b$</td>
<td>lbs/kWh</td>
<td>3.11</td>
</tr>
<tr>
<td>Energy Star Combined Energy Factor</td>
<td>$CEF_{ES}$</td>
<td>lbs/kWh</td>
<td>3.93</td>
</tr>
<tr>
<td>User Load</td>
<td>$Load_{\text{User}}$</td>
<td>loads/year</td>
<td>295</td>
</tr>
<tr>
<td>Load Weight</td>
<td>$W_{\text{load}}$</td>
<td>lbs/load</td>
<td>8.5</td>
</tr>
</tbody>
</table>
Chapter 4: Heterogeneity in time and energy use of watching television

Chapter Summary
There is substantial variability in residential energy use, partly driven by heterogeneous behavioral patterns. Time-use is relevant to energy when consumption tracks the time a device is used. Cluster analysis is a promising approach to identify time-use patterns. If clusters with particularly long time use and thus high energy consumption emerge, these groups could merit targeted policy intervention. I investigate these ideas via an empirical study of time use for television watching in the U.S. Three clusters were identified. In 2013 the average time spent watching television by Clusters 1, 2 and 3 are dramatically different: 1.1, 3.5 and 7.7 hours per day respectively. While members of Cluster 3 are only 14% of the total population they represent 34% of TV energy consumption. The population of Cluster 3 tends to be older, less employed and less educated. Energy savings per adopter is much larger for Cluster 3, suggesting much higher benefits from efficient devices. These results are relevant to the design of efficiency programs, indicating potential for variable rebates and/or tiered communication. With variable rebates, utilities would offer higher incentives to high-use customers. In tiered communication, utilities would devote more resources to engage customers with larger savings potential.
4.1 Introduction

Promoting efficiency in household behaviors is an important strategy to improve the environmental and economic performance of the energy sector. A variety of interventions are ongoing to improve energy efficiency, including standards, certifications, education, tax incentives and rebates. Utilities, local, state and federal government bodies are increasingly involved in promoting efficiency, including efforts in the commercial, residential and industrial sectors. Focusing on the U.S., utilities have more than three decades of experience running efficiency programs. Residential programs, mainly funded through approved rate increases (systems benefit charge), had expenditures of $1.7 billion in 2014, with most spent on financial incentives (54%), followed by administration and marketing at (18%), R&D at 3% and other programs (25%) (CEE 2015). Efficiency program expenditures are expected to double in the next decade (Barbose 2014). The U.S. federal government also spent $300 million for supporting state level energy efficient appliance rebate programs (SEEARP) between 2009 and 2012. Similarly, many other countries such as China, South Korea, India, Denmark, Netherlands, France, Italy, UK, Japan and Mexico have federal energy efficiency programs (Can 2011; de la Rue du Can et al. 2014).

While there are many efforts to measure the cost-effectiveness of utility efficiency programs (National Action Plan for Energy Efficiency 2008), it is difficult to conclusively estimate their contribution (Arimura et al. 2011). Whatever the current cost-effectiveness is, it is clearly desirable to improve it. One potential avenue to improve cost-effectiveness is to better account for consumer heterogeneity. Consumer heterogeneity includes differences between usage patterns of energy using devices (e.g. thermostat settings and schedule) and the technical characteristics of those devices (e.g. efficiency of air conditioner). These differences are large, e.g. living room temperature of New York households in the summer ranged from 59F to 75F (Roberts and Lay 2013). The energy savings from an efficient air conditioner will be radically different for a household with a thermostat setting of 59F compared to 75F. Peak savings will also vary widely by consumer depending on thermostat schedule.

There is thus potential to improve the cost-effectiveness of utility efficiency programs by accounting for consumer heterogeneity. However, current utility practices generally treat
consumers as a single average consumer, masking any differences in behavior or preferences. Heterogeneity implies that an efficiency measure, while cost-effective for the average, may not be cost-effective for some subgroups, but may be particularly beneficial to others. If there is significant heterogeneity, treating consumers as homogenous and using an average consumer will skew the estimates for cost-effectiveness of the program. By accounting for heterogeneity, one can lower marketing cost and/or increase participation to improve the cost-effectiveness of household efficiency programs. For the air-conditioner example above, targeting the population with higher thermostat settings could save more energy with similar program costs.

Heterogeneity is typically addressed through market segmentation approaches i.e., identifying homogenous sub-population within larger heterogeneous population (Moss, Cubed, and Fleisher 2008). One approach to segmentation is to group consumers according to common demographics, e.g. household size, income (Cayla and Maïzi 2015; Moss, Cubed, and Fleisher 2008). If the objective is to address energy use, one should group consumers according to the pattern of energy use, which may vary significantly within a specific demographic group.

The biggest challenge in addressing consumer heterogeneity is lack of data on how consumers are using different devices. In principle, different combinations of smart meters, smart power strips, load monitoring software and/or smart appliances commonly called as energy disaggregation technologies can address this problem (Carrie Armel et al. 2013). However, there are many challenges for adoption of these technologies in terms of 1) hardware cost, 2) the need for better load monitoring software and 3) privacy and security concerns. While the rate of smart meter adoption is growing, it will take some years before market saturation (Faruqui et al. 2011; FERC 2014; IEI 2014). It is not yet clear what hardware, software and calibration will be needed in addition to a smart meter to give time and device-resolved results. It is important to know the importance of heterogeneity to justify further development and investment in disaggregated energy monitoring technologies.

Time-use data presents an opportunity to understand consumer heterogeneity in energy use without an advanced energy monitoring system. Time-use data is the temporal sequence of activities that a person completes in a day, e.g. wake up at 6AM, make breakfast until 6:30 AM, and so on for an entire day, and potentially for multiple days. Time-use for an activity that
involves particular devices (e.g. television, kitchen appliances) can be mapped to the energy use of the device. Note that the relationship between time use and energy use can be more complicated depending on the device. In the US, Bureau of Labor statistics conduct the American Time Use Survey (ATUS) each year.

I aim to segment consumers based on patterns in the time-use of energy consuming devices. I explore this idea to characterize television watching in the US. Televisions contribute significantly to the residential electricity demand in the U.S., consuming 7% of national purchased electricity (EIA 2015b). For comparison, note that shares for other appliances are: space heating (8.4%), space cooling (13.2%), water heating (9.2%) and refrigeration (7.5%). Furthermore, television energy use is likely increasing since people spend more time using televisions and consumer electronics each year (BLS 2015b; Nielsen 2015) and the average screen size has increased by 17% between 2010 and 2013 (Urban et al. 2014). Results from this analysis will identify sub-groups with differing television energy use, which in turn informs utility rebate programs to encourage consumers to switch to efficient televisions. The analysis of television use, a useful case study in its own right, also serves as a vehicle to explore a general approach to characterizing heterogeneity in energy use.

4.2 Methodology and Data

4.2.1 About the Dataset
The American Time Use Survey (ATUS) is a yearly survey conducted by the Bureau of Labor Statistics (BLS) since 2003. Annual participation in the survey exceeds 11,000 respondents. Only one household member is sampled per household. The survey is conducted using computer-assisted telephone interviewing in which the respondents respond on how they spent their time on the previous day, where they were, and whom they were with. Conducting the survey via a conversational interviewing style mediated by an expert is thought to improve reporting accuracy.

ATUS defines television watching as any of the following: 1) using a television to watch video programs and movies via broadcast, cable, DVD, VCR, or the internet and 2) using a computer to watch video and 3) setting up DVD/VCR player, TiVo/DVR. In addition to the time-use
information ATUS also collects respondent’s household level socio-economic data such as age, income, sex, race, marital status and education level employment status. More information on the ATUS survey can be found on the ATUS website (BLS 2015b).

4.2.2 Model

I developed a model that uses ATUS data to divide consumers into multiple segments based on their television-watching pattern. A consumer segment with similar television watching is also called a cluster. Division into consumer segments/clusters is followed by characterization of energy use and socio-economic characteristics. Energy use characteristics are used to inform the potential energy savings from each segment, while socio-economic characteristics allow us to target segments with highest savings potential.

The model consists of three main parts, data processing, pattern classification and energy model. In the data processing stage, the sequence of start and stop times of television watching in ATUS is transformed to a box function with 0 as not watching and 1 as watching television for time bins. In the pattern classification stage, the respondents are grouped into clusters based on similarities in their television watching patterns. In this stage, the cluster characteristics such as population, time-use and socio-economic characteristics are characterized through descriptive statistics. Finally, the energy model maps time-use to energy use estimates for each cluster. Figure 4-1 illustrates the model developed and flow of data. A detailed description of the model follows.

![Figure 4-1 Description of the model developed to characterize consumer heterogeneity in TV energy use.](image-url)
4.2.3 Data Processing

The data processing stage converts the ATUS dataset into a discretized representation of when people are watching and not watching television. This discretized representation is more mathematically tractable for pattern classification. For each respondent, ATUS activity data lists the sequence of activities performed with their start and stop times. The initial step in data processing is to rewrite the activities into “Watching TV” or “otherwise”. Then a discretized television watching profile for each respondent is specified using the following function:

$$\delta(t) = \begin{cases} 
1 & \text{if Watching TV in time interval } t \\
0 & \text{otherwise}
\end{cases}$$  \hspace{1cm} (Eq. 1)

where \( t \) denotes the time interval number after dividing a 24-hour day into 256 equal intervals i.e., 5.625 minutes. The resultant pattern has a “box-like” geometry. Figure 4-2 illustrates the data processing stage for one hypothetical respondent.

![Figure 4-2 Illustration of data processing stage for one hypothetical respondent: From ATUS sequence of start and stop times to box-like binary representation.](image)

4.2.4 Pattern classification

In this stage, the binary representation of respondents’ television pattern are grouped into clusters depending on a measure describing similarities between the patterns. The goal is to develop a scalar “distance” measure of similarity between the television watching patterns, i.e. the distance is small for similar patterns and large for dissimilar patterns. In order to describe similarities, features of the pattern should be extracted. Examples of features in a pattern are the number, time and width of peaks. There are many possible measures for feature extraction; I follow a commonly used approach known as the Walsh-Hadamard transform. The idea is to transform the binary representation, as shown in Figure 4-2, into a Fourier-like frequency spectrum. The
Euclidean distance between two frequency spectrums is the measure used to describe similarity of the television-watching patterns.

To explain in more detail, the binary representation of a daily television watching pattern is a set of 256 values consisting of 0’s and 1’s. The choice of 256 time intervals came from the requirements of the Walsh-Hadamard transform to have input data of the order $2^n$. The Walsh-Hadamard transform represents the binary sequences as a superposition of basis box functions (or Walsh function). The transformation yields a set of coefficients, a 256-element vector of real numbers, each coefficient reflects the strength of contribution of a Walsh function to the superposition, equivalent to a frequency spectrum from Fourier analysis. Note that like a Fourier transform, a set of Walsh-Hadamard coefficients can be mapped back to a time profile of an activity pattern. More information on Walsh-Hadamard transform can be found elsewhere (Beauchamp 1984; Beer 1981; Walsh 1923). Application of this methodology can be widely seen in travel behavior analysis, e.g. (R. Chen 2013; Recker, McNally, and Root 1985).

Following the Walsh-Hadamard transformation, segmentation or clustering is conducted using the $k$-means algorithm (MacQueen 1967). The idea of $k$-means clustering is to pick $k$ randomly selected respondents as initial centroids on which to build clusters. Each member of the population is assigned the cluster with smallest Euclidean distance from the centroid. Given these initial clusters, a new centroid is calculated as the average of each cluster population. The process of distributing the population into clusters is repeated until there is no further reassignment to clusters. A detailed description of $k$-means clustering can be found elsewhere (Duda, Hart, and Stork 2000; Kogan 2007). For the reader interested in more technical details, note that I used weighted $k$-means clustering where weighted averages and weighted Euclidean distance were calculated. This is because the ATUS survey comes with weights that map an individual’s response to their representation in time-use of the overall U.S. population.

The result of the above process is division of the population into $k$-clusters. Next, the inverse Walsh-Hadamard transformation is used to obtain cluster average television patterns. The cluster average pattern can be interpreted as the probability of an average cluster member watching television at a particular time of day. An alternate interpretation is what fraction of the cluster is
watching television at a particular time. Given cluster membership, cluster characteristics are
estimated using descriptive statistics. The cluster characteristics measured includes population of
the clusters, time-use characteristics such as total television viewing time and number of times
television watched in a day, socio-economic characteristics such as age, gender, income,
education, marital status, employment status and number of household members and etc. Survey
weights are used to normalize the results to represent the U.S. population.

Given the number of clusters \( k \), the above procedure describes how to divide the population into
\( k \) clusters. However, it is not clear \textit{a priori} what value \( k \) should take, i.e. how many clusters are
ideal. Obviously higher \( k \) reduces distances of members from centroids i.e. clusters are more
homogenous. However, the objective is to find the smallest value of \( k \) that succinctly describes
heterogeneity. The following procedure summarizes the methodology to identify the ideal
number of clusters \( k \). For any given number of clusters, cost is defined as the summation of the
weighted distance between all the respondents to their closest cluster center. To identify the ideal
\( k \) value, a cost function is developed. The cost function provides the cost for a set of cluster
numbers, \( y = \{2,3,4 \ldots n < N\} \) where \( N \) is the number of observations in the dataset. The cost
function always decreases monotonically. Therefore, a range of \( k \)-values are initially chosen
based on when there is a turning point in the marginal reduction in cost from increasing \( k \), i.e. the
“knee point of the curve”(Theodoridis and Koutroumbas 2008). For the range of \( k \)-values
chosen, detailed cluster characteristics are found. The best \( k \) among these is chosen as the value
for which every cluster is clearly distinguishable based on the cluster characteristics.

4.2.5 Energy Model

The goal of the energy model is to measure total energy use of each cluster and the expected
marginal energy savings when a member of a cluster upgrades to an efficient television. The
baseline year for the energy model is 2013.

Total energy use of each cluster for television watching in the year 2013 is calculated using the
formula shown in Eq. 2.

\[
\text{Total Energy use}_k = p_k \times (t_k \times W_{\text{active}} + (24 - t_k) \times W_{\text{standby}})
\]  

(Eq. 2)
where \( k \) is the number of clusters identified; \( p_k \) is the population of each cluster; \( t_k \) is the total time spent watching television for each cluster; \( W_{\text{active}} \) is the power consumption of an average 2013 TV and \( W_{\text{standby}} \) is the standby power. I neglect heterogeneity in television models and use an average active and standby mode power consumption values. (Urban et al. 2014) reports the average active power consumption as 90W and 1.6W in standby mode for the year 2013. Note that differences between clusters in terms of television ownership (technology, vintage and screen size) are not covered in ATUS. While a possible topic for future work, here I isolate the effect of watching pattern heterogeneity on television energy use.

Per person or marginal energy saving per cluster is given by Eq. 3

\[
Marginal \; Energy \; Savings_k = t_k \times (W_k - eW_k)
\]  

(Eq. 3)

where, \( eW_k \) is the active power consumption of the efficient TV. The efficient TV is assumed to be 40 inch LCD TV compliant with Energy Star V7.0, which will become effective October 2015 (EPA 2015). Note that ENERGY STAR compliant televisions accounted for 84% of the sales in 2013, 96% of these 32.9 million units were LCD televisions (EPA 2014). Also, the average size of the television stock has been increasing, 29 inches in 2010 and 34 inches in 2013 (Urban et al. 2014) I draw on Energy star requirements to determine the power consumption of the efficient television \( eW_k \). The efficient television is taken to meet ENERGY STAR specification V7.0 with a 40-inch TV an aspect ratio of 16:9, resulting in maximum active power consumption of 37.6W. I assume this is a reasonable measure of the average power consumption, thus \( eW_k = 37.6W \).

4.2.6 Literature review

While there are a variety of works linking time and energy use (Torriti 2014), none of these studies characterize time-use, and in turn, energy-use heterogeneity. To briefly summarize prior work, (Schipper et al. 1989) discuss qualitative differences between breakdown of energy use and time use for different activities. The earliest time-use based energy model was developed by (Capasso et al. 1994). They use a probabilistic approach to model activity pattern of each household. Since a time-use survey only provides information about a single person in a household, probability of an activity to be performed in a household is modeled based on
demographic characteristics of individual member in the household. The synthesized activity data is mapped onto different end-use technologies to generate residential load curves. Recent extensions of (Capasso et al. 1994) include the use of probabilistic and/or stochastic techniques to accurately synthesis activity data for households. Many researchers ((Johnson et al. 2014; Muratori et al. 2013; Richardson et al. 2009; Richardson, Thomson, and Infield 2008; Widén, Nilsson, and Wäckelgård 2009; Wilke et al. 2013) use Markov chain approach to predict activity of an individual with particular demographic characteristic. (Subbiah et al. 2013) classifies individual based on their demographic and uses a probabilistic model to predict activity of each class. (Chiou et al. 2011) uses a bootstrap sampling method to derive activity profile of individual in a household.

Validation of these approaches have shown that mean time for any activity can be predicted with high degree of confidence however diurnal variations (peak energy use) are not accurately preserved. This shortcoming is attributed to the inability of the model to address heterogeneity in activity pattern of the household. Furthermore, mapping time-use survey defined activities to end-use technology can be problematic. For example, accurately mapping cooking activity to energy use requires further information on type of food cooked, the efficiency of the equipment used and number of minutes each equipment is on. Therefore, insufficient data and heterogeneity in the physical characteristics of equipment contribute to model inaccuracy.

The policy intent of the aforementioned models has been to inform decisions on demand response, energy efficiency and microgrid implementation programs. The application of these models included visualizing load curves for different attributes such as building type (attached vs. detached), type of day (weekend vs weekdays and winter vs summer), occupancy, household type (family vs single, or working household vs non-working household). However, no definite or strong policy connections with respect to these attributes were made.

Some researchers use time-use surveys to focus on the activity specific implication on energy use or energy implications of a specific group of consumers (López-Rodríguez et al. 2013). (Torriti 2012) studied occupancy variance with time-of-day of single-person households in 15 European countries. According to him, during peak times (8PM-8:10PM), most single-family households
were watching television. In Spain, television watching is the activity with highest simultaneous percentage of household involvement during peak hours (Santiago et al. 2014). Other time-use application includes quantifying the economic impact of harmonic losses from audio visual devices in the residential sector (Santiago et al. 2013).

To summarize, while these models provide new ways to link time-use with equipment-specific energy use, they did not do the following: 1) address heterogeneity in the end-use technology usage pattern, 2) link demographic with the heterogeneous usage pattern and 3) connect to policy with respect to consumer heterogeneity. I address these three points in this paper.

Addressing heterogeneity through market segmentation has a long history. In utility energy efficiency programs, market segmentation models have focused on segmenting customers by demographic variables. Sometimes researchers also segment based on lifestyle and/or attitude of the population (Moss, Cubed, and Fleisher 2008; Stern et al. 1986). These approaches were used for marketing purposes only. However, by addressing heterogeneity, utilities can re-structure their planning and marketing strategies of the energy efficiency programs. To our knowledge this is the first work to segment population based on the time-use (and thus energy use) pattern, followed by socio-economic characterization of the segments.

4.3 Results and Discussion
The model described in section 2 was built in MATLAB. The model outputs for input data corresponding to year 2013 are discussed in this section.

4.3.1 Cost function for different numbers of clusters
The cost function as function of cluster number k is shown in Figure 4-3. As discussed in section 2.4, the ideal number of clusters is at the knee of the curve, in this case between 3 and 6. In order to choose the best k value, the average time spent and watching pattern of the subgroups were compared for  \( k = \{3,4,5,6\} \). For the best k value, all sub-groups are distinguishable in time spent and watching pattern. \( k = \{4,5,6\} \) were rejected because there were at least two very similar subgroups for each. See Figure S1 in the supporting information for results when \( k=4 \). The best value of k was thus chosen to be 3.
4.3.2 Heterogeneity in television watching pattern

The sample of respondents is divided into 3 clusters whose average television-watching patterns are shown in Figure 4-4 along with the average pattern of the total population. The y-axis of the Figure 4-4 can be interpreted as either the watching pattern of an average person in the cluster or the percentage of population in the cluster watching television. In addition, the Figure 4-4 also summarizes cluster characteristics such as, population, average time spent watching television and average number of television watching activity (frequency). The clusters are sorted in ascending order based on average time spent watching television and named cluster 1, cluster 2 and cluster 3 respectively.

According to the American Time Use Survey, the percentage of people watching television increases gradually from 7AM until 4PM. The share of population then increases swiftly and reaches a peak at around 7:45PM, where 40% of the population watches television. After the peak, share of population decreases progressively until 4AM.

Heterogeneity in television time-use is significant. An average person in cluster 3 spends almost three times more time watching television than the average person in the total population, 2 hours and 46 minutes. Further there are significant differences between the clusters regarding the television watching peak. Cluster 1 does not have a distinct peak compared to clusters 2 and 3. It is interesting to note that the peak of cluster 2 occurs approximately at 8PM the same time as the peak of average watching pattern of total population. Again cluster 3 has a distinct watching pattern with multiple peaks at 3PM and 6:45PM.
Dividing the population based on time-use results in larger heterogeneity than demographic-based segmentation. For example, using the same ATUS data, television watching time varies between 2 to 4 hours when segmenting based on different age groups (BLS 2015a).

Based on the average time and population characteristics, energy use of clusters 1 to 3 were calculated to be 23, 36 and 31 GWh/day respectively. Figure 5a shows the energy use and population of each cluster as a percentage of their total. The result shows that even though cluster 1 has the most population they contribute the least to the total energy while cluster 3 has the lowest population of 14% but contributes the second most 34% to the total energy. Heterogeneity in the total time spent watching television is the driving factor for differences in energy use. Time-use for other energy-consuming devices will presumably have different degrees of heterogeneity, those devices with large heterogeneity are obviously those most important for the cluster analysis developed here.

Figure 5b shows the marginal energy savings when an individual’s television (90W_{active} and 1.6W_{standby}) is replaced by an efficient television (37.6W_{active} and 1.6W_{standby}). The marginal energy savings potential from targeting one individual in cluster 3 is 7.1 times and 2.2 times
greater than targeting an individual in clusters 1 and 2 respectively. Further the savings from clusters 2 and 3 could reduce peak demand (see Figure 4-4). These results show that Cluster 3 is a suitable candidate for targeted policy interventions.

Figure 4-5 Summary energy use statistics of the clusters. A) Total energy use of televisions watched by respondent in each cluster. B) Energy saving from replacing television in one household with efficient 2015 model. The range refers to the standard deviation of television watching time within cluster.

4.3.4 Socio-economic characteristics of the clusters

In order to understand membership in the clusters, I analyzed a number of socio-economic variables of the respondent and their household. Here I show results for only those variables with significant differences between the clusters. Other socio-economic characteristics can be found in the supporting information.

Results for employment status of respondent, marital status or unmarried partner, employment status of partner, income, age and education level of respondent are shown in Figure 4-6. Compared to clusters 1 and 2, cluster 3 is significantly different with respect to a number of socio-economic factors. Cluster 3 consists of population who are older, less educated and largely unemployed or holding part-time employee status, relative to other clusters. The major differences between cluster 1 and 2 are the employment status of the cluster members and their partners and the number of younger children present in the household. Compared to cluster 2, cluster 1 has a higher share of employment for both the respondent and their partner. Cluster 1 households also have more children (less than 18 years old) compared to cluster 2. The average
age of the youngest child in cluster 1 is also lower than cluster 2. For other socio-economic characteristics, the difference between Cluster 1 and 2 are minor. Figure 4-6 contains four subfigures that summarize demographic differences.

Employment: Figure 4-6a shows the employment status of respondent and their spouse or unmarried partner. Clusters 1 and 2 consists of at least 2 and 1.7 times more percentage of population employed when compared to cluster 3. In addition, more than 50% of those employed in cluster 3 are part time workers while clusters 1 and 2 consists of 20% and 25% respectively. Therefore, television time spent is inversely related to employment status. There is no significant variability between the clusters with respect to the percentage of population married or living with unmarried partner. However, the employment status of the partners follows similar trend as the employment status of the respondent. Cluster 3 consists of larger percentage of partners unemployed or working part time. The employment of respondent and their spouse or unmarried partner may indicate less leisure time in the household therefore lesser time for watching television.

Income: Figure 4-6b shows the annual income distribution of the employed population in each cluster. The results are summarized for only those individuals who reported being employed. Since cluster 3 has a relatively larger population unemployed or working part time lower income is expected for that cluster compared to clusters 1 and 2. The results indicate the same.

Age: Figure 4-6c shows the distribution of age groups in each cluster. The median age of cluster 1, 2 and 3 are 41, 49 and 54 years. The age distribution is skewed to the left as I move from cluster 1 to 3.

Education: Figure 4-6d shows the education status of each cluster. As employment status and income are correlated with educational level, the prior results on income and employment suggest that the education status of cluster 3 is lower than clusters 1 and 2. As expected, the results show the same more than 60% of cluster 3 are either studying or high school graduate while only 40% fall in the same category for cluster 1 and 2. Also, clusters 1 and 2 have higher share of people with bachelors and graduate degree compared to cluster 3.
Other demographic characteristics analyzed include number of children in household, age of the children, metropolitan status of the household, number of household members, worker class. The results for these variables can be found in the supporting information.

To summarize, while clusters are to some degree demographically distinct, there is significant variability within each cluster. While more advanced statistical analysis would help link demographics and clusters, our impression is that there would still be still be significant variability not explained by demographics. This suggests that data on end-use consumption per device using smart home systems show promise to identify heterogeneity in the energy using behaviors.

Figure 4-6 Summarizes the socio-economic characteristics of the clusters. Figure 4-6a - Employment status of the respondent and their spouse or unmarried partner categorized by clusters. Figure 4-6b - Annual individual income distribution of the employed respondents categorized by clusters (in 2013 dollars). Figure 4-6c - Age distribution of the respondents categorized by clusters. Figure 4-6d - Education status of the respondents categorized by clusters.
4.3.5 Multi-year results
Since ATUS data is available for the years 2003-2013, I analyzed heterogeneity in time-use pattern for all the 11 years. Both time-use trends and socio economic-characteristics have remained consistent for the past 11 years. Multi-year results are available in the supporting information.

4.3.6 Caveats and uncertainty
One key caveat is that the television time-use per respondent reported in ATUS may be underreported. ATUS does not report on secondary activities. In other words, respondents could be doing two activities at the same time (e.g., cooking and watching television, taking care of children and watching television) and the respondent could consider television activity as secondary activity. Additionally, television “On Time” when respondent is away from the television is also not recorded in ATUS.

This model does not represent the television energy use of the entire household, only that of the device watched by the survey respondent. This is because the ATUS only covers the behavior of the respondent, not the entire household and does not include television-watching time of household members less than 15 years old.

The analysis does not account for differences in the televisions ownership of the clusters. I assume all televisions are typical. Accounting for differences in televisions owned would increase heterogeneity, but the variability between clusters would only increase if there were differences in the types of televisions owned in different clusters. Such differences could be significant, since clusters 1 and 2 have higher median income, they might own larger televisions. On the other hand, since cluster 3 watches more television, member may devote a larger share of their income to purchasing newer and larger models. Limited survey data does not allow us to pursue this question of differences in television models.

It is also important to note that time-use based approaches work best when the “On time” of the device correlates with the amount of time of a reported activity. Energy use of white goods such as refrigerators and washing machines dryers, for example, does not map well to time use. For these devices, data from other survey instruments such as RECS are more appropriate.
4.4 Conclusions and Policy implications

Our results indicate that accounting for customer heterogeneity could significantly improve the benefit-cost ratio of utility programs to incentivize energy efficiency. Every adoption by a customer in Cluster 3 saves approximately triple the total energy compared to an average customer. Utilities are also often motivated to reduce peak energy usage and there are dramatic differences in peak profiles between clusters. It is thus in the interest of utilities to identify and target those customers whose adoption will benefit them most.

The benefits of preferential adoption of televisions by Cluster 3 will vary by utility, but I illustrate via an estimate of potential monetary savings for Pacific Gas and Electric (PG&E) in California. The monetary savings is calculated as the difference in electricity wholesale purchases for distributing 644,000 energy efficient televisions (14% of PG&E residential accounts) uniformly among the population versus targeted adoption by Cluster 3. While the number of televisions in each household is reported as 2.6 (Urban et al. 2014), I assume a conservative case where only the primary television is replaced. The television watching patterns of residents for the uniform distribution follows the average patterns shown in figure 4. Assuming energy efficient televisions draw 52 Watts less power (EPA 2015), preferential adoption by Cluster 3 reduces power consumption in the PG&E area depending on time of day, up to a maximum of 20 MW, at 3 PM. Using daily profiles of wholesale electricity prices, this reduction in load saves PG&E $2-3 million annually. Given that consumers tend to own televisions for 7 years, this cost savings translates into utilities being willing to pay up to $21-33 per customer for preferential adoption by Cluster 3.

How can utilities identify and target sub-populations for energy efficiency programs? To first discuss identifying sub-populations, there are tradeoffs between the accuracy of identification and costs. I propose three approaches, in increasing order of cost to the utility and quality of data.

The least expensive method to identify sub-populations is to use ATUS and other public data to associate Cluster 3 consumers with demographic characteristics of their customers. While the data is free, as seen in section 3.4, Cluster 3 does not align perfectly with demographic characteristics. For example, elderly customers are far more likely to be in Cluster 3, but many
are not. While ATUS data does not inform use of most appliances, a similar analysis as done here but for the Residential Consumption Energy Survey (RECS) would inform customer heterogeneity in thermostat settings, lighting, and use of washers and dryers.

A second approach is that utilities could conduct their own surveys of appliance use. This would allow utilities to map energy relevant behavior to individual customers instead of demographic groups, but incur the cost to administer the survey. Also, there is a question of the accuracy of self-reported information.

Thirdly, smart sub-metering combined with surveys would increase the accuracy of data and enable better verification of the benefits of targeting programs. Starting from least to most expensive, three metering solutions are temporary smart meter, permanent smart meter, and smart meter with plug-load sub meters. The temporary smart meter approach is being tested in the U.K. by the University of Cambridge’s Environmental Change Institute (ECI). The program involves combining a 3-day loan of a smart meter with a time-use survey (Environmental Change Institute 2016). While there are hopes that Non-Intrusive Appliance Load Monitoring methods (NLIM) can leverage smart meters to inform appliance level load information, the methods still have problems with accuracy (Carrie Armel et al. 2013). Separate plug load meters could remove the need for surveying customers, but involve additional hardware investment.

The above methods enable a utility to identify a subset of customers to target for an efficiency program. Strategies are needed to increase the adoption of the technology in the targeted population. Variable rebates and tiered communication are two possible strategies. With variable rebates, utilities would offer higher rebates to high-use customers for whom efficiency would deliver larger benefits to the energy system. There is a long history of utilities tailoring incentives by location to address specific infrastructure constraints, e.g. RG&E Control Your Savings program (RGE 2015). In the demographic space, enhanced incentives for lower income and elderly populations are reasonably common. Tailoring an incentive to the benefits an individual household would deliver to a utility would be new, but the prior two examples show precedent for the principle.
Utilities can also use tiered communication to target distinguished segments of customers. Tiered communication means the degree and type of information varies according to customer type. In order of increasing expense, utility’s means of customer communication are the following: website, email, modified utility bill, flyer mailed with utility bill, separate mailing, phone, and in person. A tiered communication strategy would allocate resources so as to encourage participation in those groups whose adoption most benefit the utility. For example, for televisions, every consumer might receive brief information on the utility bill about the rebate, but cluster 3 customers might receive a phone call. In order to establish a customer dependent degree of savings, the application for rebate should ask simple questions to establish usage patterns.

I thus suggest that utilities engage in benefit-cost analysis of variable rebates and tiered communication strategies for energy efficiency programs. Currently, in the U.S., 26 programs provide rebates for televisions while around 200 and 500 programs are available for refrigerators and lighting respectively (EPA 2015). Re-evaluation of the programs would presumably affect the number and design of programs for each end-use technology. I do not demonstrate such an analysis here; this would require detailed and utility dependent data, not publicly available. I have, however, demonstrated the potential benefits of such an approach for televisions. Analysis of heterogeneity in energy use for other devices and appliances, e.g. heating and cooling systems, would presumably also reveal benefits of a more personalized approach to consumers.

4.5 Supporting Information

4.5.1 Introduction
American Time Use Survey (ATUS) was conducted for the years 2003 to 2013. Television watching pattern for all the years were analyzed using the methodology discussed in the main text (Section 2). The supplementary information summarizes 1) results from cost function and subsequent determination of the ideal number of clusters, 2) multi-year results on television watching pattern and 3) socio-economic characteristics for each cluster. As it can be concluded from the results the TV watching pattern and socio-economic characteristics have remained constant throughout the survey year therefore only 2013 results were reported in the main text.
4.5.2 **Ideal number of clusters**

To determine the ideal number of clusters (sub-groups) a cost function was generated as shown in Figure 4-3 in the main text. The x-axis of the cost function is the number of clusters ($k$) and y-axis is the cost associated for each $k$ value. Cost is the total sum of distance between each centroid and their respective cluster members. The sum of distances or the cost decreases with increase in $k$. The ideal value of $k$, is assumed to be when the time spent and the watching pattern of each sub-groups are substantially distinguishable. The monotonically decreasing characteristic of the cost-function allows for identification of a range for the ideal $k$ values. The range occurs at the knee of the curve where an additional increase in the number of clusters lead to a marginal reduction of the cost. In this case, the $k$ can take a value between 3 to 6. For each value of $k$, the average time spent and watching pattern were compared. For $k$ greater than or equal to four there were atleast two clusters that were indistinguishable. Fig. S4-1 and Fig. S4-2 shows television watching pattern and distribution of the time spent watching television for $k=4$ i.e., when ATUS data is divided into four subsets based on $k$-means clustering. The result shows that the average time pattern of the 4 clusters are distinct however cluster 1 and 4 are not significantly different from each other. Similarly, the average time spent by cluster 1 and 4 as marked as red-dotted line in Fig. S4-2 are not significantly different from each other. For any $k$ value, greater than 4 the same phenomenon exists. Therefore, ideal value for $k$ was determined as 3 since all the three clusters were significantly different (See Figure 4-4 in main text).

![Average television watching pattern from ATUS in 2013 when the number of clusters, k = 4.](image)

Fig. S4-1 Average television watching pattern from ATUS in 2013 when the number of clusters, k = 4.
4.5.3 Multi-year results

4.5.3.1 TV watching pattern.

The TV watching pattern from the multi-year data was clustered into 3 segments based on the cost function developed in the main text (Figure 4-3). Fig. S4-3 to Fig. S4-5 are average TV watching pattern of Clusters 1, 2 and 3 respectively. Cluster 1 represents those who do not or watch TV for a short duration. Cluster 2 watches TV more than Cluster 1 and the TV watching activity occurs after 4PM and goes until midnight. Individuals in Cluster 3 spend the most time on TV. They watch TV almost all day starting 8:00AM upto midnight. The TV watching pattern of each cluster are relatively constant throughout the years.
Fig. S4-3 Television watching pattern of Cluster 1 between year 2003 and 2013

Fig. S4-4 Television watching pattern of Cluster 2 between year 2003 and 2013
4.5.3.2 Cluster characteristics.

The important characteristics of the TV watching pattern clusters are 1) percentage of population in each cluster, 2) Number of times or TV watching frequency and 3) total time spend on TV. Fig. S4-6 to Fig. S4-8 shows those characteristics respectively. These characteristics represent the U.S. population.

Population of each cluster: Percentage of population in each cluster is constant throughout the years. Cluster 1 is the most populated segment with 56% in 2003 and gradually decreasing to 53% in 2013. Considering the variability and uncertainty the 3% decrease should not be concluded as a trend. Cluster 2 is the second most populated segment with a constant a value of 32% throughout the years and Cluster 3 consisted of the remaining 11-13% depending on the survey year. From this result, I can conclude that most population in the U.S. spend less time on TV.
TV watching frequency: The average TV watching frequency for cluster 1, 2 and 3 are 1, 1.8 and 2.7 respectively. The distribution of the frequency shows the 40% of the population in Cluster 1 did not watch TV while the same group in clusters 2 and 3 are insignificant. 10% of Cluster 1 also reported watching TV more than once and their average TV watching duration is 2 hours and 31 mins. More than 70% in cluster 2 reported watching once or twice while Cluster 3 has more than 90% watching TV twice or more. Table S1 shows the standard deviation (SD) values for each year and each cluster. Distribution of Clusters 1 and 2 are similar and smaller than Cluster 3. SD values also show that the distribution between each year for the respective cluster is approximately constant.

TV watching duration: From the frequency result and TV watching pattern it is evident that TV watching duration increases as I move from cluster 1 to 3. In average, clusters 1, 2 and 3 spends 1, 3.5 and 7.5 hours watching TV. Table S2 shows the standard deviation (SD) values for each year and each cluster for TV watching duration. The distribution gets wider as I progress from cluster 1 to 3. Similar to the results above, the distribution between the years for respective cluster is approximately constant.

Fig. S4-6 Multi-year population ratio of each cluster
Fig. S4-7 Multi-year TV watching frequency of each cluster

<table>
<thead>
<tr>
<th>Year</th>
<th>Cluster 1</th>
<th>Cluster 2</th>
<th>Cluster 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>2003</td>
<td>0.96</td>
<td>0.94</td>
<td>1.19</td>
</tr>
<tr>
<td>2004</td>
<td>1.00</td>
<td>0.91</td>
<td>1.23</td>
</tr>
<tr>
<td>2005</td>
<td>0.99</td>
<td>0.95</td>
<td>1.19</td>
</tr>
<tr>
<td>2006</td>
<td>0.98</td>
<td>0.94</td>
<td>1.20</td>
</tr>
<tr>
<td>2007</td>
<td>0.96</td>
<td>0.92</td>
<td>1.12</td>
</tr>
<tr>
<td>2008</td>
<td>0.98</td>
<td>0.97</td>
<td>1.24</td>
</tr>
<tr>
<td>2009</td>
<td>0.97</td>
<td>0.97</td>
<td>1.19</td>
</tr>
<tr>
<td>2010</td>
<td>0.98</td>
<td>0.94</td>
<td>1.13</td>
</tr>
<tr>
<td>2011</td>
<td>0.96</td>
<td>0.93</td>
<td>1.18</td>
</tr>
<tr>
<td>2012</td>
<td>0.96</td>
<td>0.95</td>
<td>1.15</td>
</tr>
<tr>
<td>2013</td>
<td>0.95</td>
<td>0.92</td>
<td>1.12</td>
</tr>
</tbody>
</table>

Table S4-1. Multi-year standard deviation values for TV watching frequency of each cluster
Fig. S4-8. Multi-year TV watching time statistics of each cluster. For X-axis values of the distribution figures please refer to the legend.

<table>
<thead>
<tr>
<th>Year</th>
<th>Cluster 1</th>
<th>Cluster 2</th>
<th>Cluster 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>2003</td>
<td>1.22</td>
<td>1.64</td>
<td>3.14</td>
</tr>
<tr>
<td>2004</td>
<td>1.30</td>
<td>1.61</td>
<td>3.13</td>
</tr>
<tr>
<td>2005</td>
<td>1.25</td>
<td>1.65</td>
<td>3.11</td>
</tr>
<tr>
<td>2006</td>
<td>1.27</td>
<td>1.59</td>
<td>3.08</td>
</tr>
<tr>
<td>2007</td>
<td>1.20</td>
<td>1.69</td>
<td>3.04</td>
</tr>
<tr>
<td>2008</td>
<td>1.28</td>
<td>1.70</td>
<td>3.16</td>
</tr>
<tr>
<td>2009</td>
<td>1.24</td>
<td>1.66</td>
<td>3.22</td>
</tr>
<tr>
<td>2010</td>
<td>1.25</td>
<td>1.69</td>
<td>3.10</td>
</tr>
<tr>
<td>2011</td>
<td>1.24</td>
<td>1.71</td>
<td>3.21</td>
</tr>
<tr>
<td>2012</td>
<td>1.27</td>
<td>1.74</td>
<td>3.15</td>
</tr>
<tr>
<td>2013</td>
<td>1.27</td>
<td>1.75</td>
<td>3.24</td>
</tr>
</tbody>
</table>

Table S4-2. Multi-year standard deviation values for TV watching time of each cluster
4.5.3.3 Socio-economic characteristics

This section summarizes the results of socio-economic categories analyzed. Only important socio-economic characteristics were analyzed.

Age:

The multi-year mean age of each cluster generally follows an increasing trend. Fig. S4-9 shows the multi-year average age and distribution of the clusters. Cluster 1 consists of the youngest population with mean age increasing from 41 to 42 during the years 2003 to 2013. Cluster 2 is the second youngest segment with mean age increasing from 46 to 48. Cluster 3 consists of the older population whose mean age increased from 48 to 51. Table S3 summarizes the Standard deviation of age. The age distributions of clusters 1 and 2 follow a normal distribution around their respective mean with SD values around 17 and 18.5 respectively. Cluster 3 is slightly skewed to the right therefore median of cluster 3 is expected to be higher than the mean. The age statistics indicate that, TV watching duration or frequency is proportional to age.

Fig. S4-9. Multi-year summary of age statistic for each cluster
<table>
<thead>
<tr>
<th>Year</th>
<th>Cluster 1</th>
<th>Cluster 2</th>
<th>Cluster 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>2003</td>
<td>16.85</td>
<td>18.12</td>
<td>20.70</td>
</tr>
<tr>
<td>2004</td>
<td>16.60</td>
<td>18.56</td>
<td>20.67</td>
</tr>
<tr>
<td>2005</td>
<td>16.98</td>
<td>18.12</td>
<td>21.70</td>
</tr>
<tr>
<td>2006</td>
<td>16.94</td>
<td>18.29</td>
<td>21.20</td>
</tr>
<tr>
<td>2007</td>
<td>16.81</td>
<td>18.31</td>
<td>21.41</td>
</tr>
<tr>
<td>2008</td>
<td>17.13</td>
<td>18.16</td>
<td>20.26</td>
</tr>
<tr>
<td>2009</td>
<td>16.94</td>
<td>18.56</td>
<td>20.75</td>
</tr>
<tr>
<td>2010</td>
<td>17.07</td>
<td>18.50</td>
<td>20.96</td>
</tr>
<tr>
<td>2011</td>
<td>17.27</td>
<td>18.36</td>
<td>20.62</td>
</tr>
<tr>
<td>2012</td>
<td>17.21</td>
<td>18.73</td>
<td>20.77</td>
</tr>
<tr>
<td>2013</td>
<td>17.42</td>
<td>18.59</td>
<td>20.54</td>
</tr>
</tbody>
</table>

Table S4-3. Multi-year standard deviation of age for each cluster

Children:
The multi-year statistics of mean number of children for the clusters are shown in Fig. S4-10.
The mean of the multi-year average number of children for clusters 1, 2 and 3 are 0.91, 0.68 and
0.57 respectively. The number of children statistic gradually decreases throughout the years
although the clusters are clearly apart from each other. The distributions of the mean number of
children are similar between the clusters. This result points out that, more children in household
equal lesser TV watching duration. In addition, multi-year mean age of the youngest children of
each cluster is shown in Fig. S4-10. The result shows that cluster 1 has the youngest children
followed closely by cluster 2 and cluster 3. This result implies that younger the children lesser
the TV watching duration. Age of the youngest children roughly follows a uniform distribution.
Fig. S4-10. Multi-year statistic of the number of children in household for each cluster. Children are defined as anyone less than 18-year-old.
Fig. S4-11. Multi-year statistic on the age of youngest household children for each cluster

Employment

This section summarizes the multi-year employment status of the respondent and their partner (either spouse or unmarried partner). Fig. S4-12 shows the results in the following in order 1) ratio of respondents employed, 2) ratio of respondent working full time, 3) ratio of respondents working more than 40 hours in a week, 4) ratio of respondents living with their partner, 5) ratio of partners employed and 6) ratio of partners working fulltime. Note that results 1-4 are absolute measure of the ratio of respondents while results 5 and 6 are absolute measures of the ratio of respondents living with their partner.

Clusters 1 and 2 have higher employed population with a mean of 70% and 61% respectively compared to Cluster 3 at 38%. Similarly, higher percentage of population are working full time in Cluster 1 and 2 with a mean of 55% and 49% compared to Cluster 3 at 25%. The same trend is applicable to the number of people working more than 40 hours. This result implies that in an average full-time employee spend less time watching TV. Approximately 57%, 60% and 47% of
the populations in clusters 1-3 are living with spouse or unmarried partner respectively. Out of the population living with their partners 41%, 38% and 23% of the partners are employed and fulltime employed partners make up 33%, 30% and 18% of the population of partners in clusters 1-3 respectively. The employment statistics of the partners show similar trend to the respondents. Table S4-4 presents the average multi-year statistics on the employment status.

In addition to the results discussed above, worker class of the respondent was analyzed. The result does not help in differentiate the clusters. Most population of each cluster worked in a private, for profit firm followed distantly by local government job and self-employment. The results are shown in the Fig. S4-13.

<table>
<thead>
<tr>
<th></th>
<th>Cluster 1</th>
<th>Cluster 2</th>
<th>Cluster 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratio of respondents employed</td>
<td>0.70</td>
<td>0.62</td>
<td>0.36</td>
</tr>
<tr>
<td>Ratio of respondent working full time</td>
<td>0.55</td>
<td>0.49</td>
<td>0.26</td>
</tr>
<tr>
<td>Ratio of respondents working more than 40 hours in a week</td>
<td>0.35</td>
<td>0.35</td>
<td>0.21</td>
</tr>
</tbody>
</table>

Fig. S4-12. Multi-year statistics on employment status of respondent and their partner for each cluster
<table>
<thead>
<tr>
<th></th>
<th>Cluster 1</th>
<th>Cluster 2</th>
<th>Cluster 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratio of respondents living with their partner</td>
<td>0.58</td>
<td>0.61</td>
<td>0.47</td>
</tr>
<tr>
<td>Ratio of partners employment</td>
<td>0.41</td>
<td>0.39</td>
<td>0.24</td>
</tr>
<tr>
<td>Ratio of partners working fulltime</td>
<td>0.33</td>
<td>0.31</td>
<td>0.18</td>
</tr>
</tbody>
</table>

Table S4-4. Average multi-year statistics on employment status of respondent and their partner for each cluster

Fig. S4-13. Multi-year statistics on employed respondent’s worker class of each cluster

Respondent Income

Fig. S4-14 represents the multi-year statistics on average annual income and distribution for each cluster. The income results are not adjusted for inflation therefore an upward trend of average income is observed. As expected the income statistics of each cluster follows the employment status trend discussed in previous sub-section. The mean income of clusters 1 and 2 increased are similar and it increased from $36000 to $46000 in 11 years. The mean income of cluster 3 increased from $30000 to $37000. The distribution of cluster 1 and 2 resemble a normal distribution whereas cluster 3 is slightly skewed to the right.
Education

Fig. S4-15 shows the education level of the respondents in each cluster. Education levels are categorized into 1) studying K-12 or high school graduate, 2) attending some college or associate’s degree, 3) Bachelor’s degree and 4) Graduate degree. The education result follows employment status and income trends. Clusters 1 and 2 are highly qualified compared to cluster 3. Clusters 1 and 2 have approximately the same percentage of population in each education category. Cluster 3 has fewer degree holders compared to other clusters.
Other socio-economic characteristics

In addition to the results discussed above few other characteristics such as marital status, type of household, number of household members and metropolitan status of the respondent’s current residence were analyzed. The results for these variables did not aid in further understanding of the clusters.

*Metropolitan status:* Fig. S4-16 represents the distribution of results for the question, “is the respondent living in a metropolitan area?” The definition for metropolitan status was changed therefore the results are not consistent before 2005.
Fig. S4-16. Multi-year Metropolitan status of the respondent of each cluster

**Number of Household Members:** TV watching pattern does not depend on the number of household members. Fig. S4-17 shows the average number of household members and their distribution.

Fig. S4-17. Multi-year average number of household members of each cluster
Marital Status: Fig. S4-18 shows multi-year marital status of each cluster. The result shows that television-watching pattern does not depend on marital status of respondent.

Fig. S4-18. Multi-year statistics on marital status of each cluster
Chapter 5: Conclusion

In this dissertation, lifestyle, measured primarily by how people spend their time (time use), is analyzed to understand the U.S. energy consumption trends and also inform various avenues of energy policy. Following paragraphs summarizes key results, future work, and conclusions.

In the second chapter, lifestyle shifts measured as time use changes between the years 2003 and 2012 were analyzed and the time use shift induced energy changes in residential, non-residential and transportation sector were quantified using decomposition analysis. Decomposition analysis allows for studying inter-dependencies between the sectors. A key result is that an average American in the year 2012 is observed to spend more time at home (19 hours) by compensating time in travel (3 hours) and out of home activities (16 hours). These time use shifts induce a net-decrease in energy consumption in the U.S, approximately 1.8% of total U.S. energy consumption in 2015. Further, the rate of lifestyle shifts between various demographics suggests a considerable heterogeneity across the population. For the years 2003 and 2012, the increase in time spent at home for population aged between 18-24 are almost twice that of the average population. Older sub population (aged more than 65) have a trend reversal, i.e., less time at home and more time traveling and out-of-home. The lifestyle shifts are observed to be primarily driven by information and communication technologies (ICT). Increased residential time is mainly due to more work at home, video and computer use, reduced time in commercial buildings is primarily due from shifting work to home and less retail shopping.

The results come with a key caveat, that they represent first order effects of lifestyle shifts. Embodied energy of the products is not accounted in the framework. Energy consumed for imported services (e.g., online supply of digital content) are also not included in the analysis. Further, the current framework measures only the aggregated effects of the sectors. Therefore, energy changes within the sectors are not quantified. Future work should focus on a disaggregated model that can explain the second order effects.

Given the advent of ICT, especially autonomous vehicles, and ride sharing, lifestyle shifts are expected to occur at a rapid rate. Analysis based on lifestyle (time use) can help in forecasting
energy trends. The results have two policy implication. 1) Prioritization of policy based on expected lifestyle shifts. If the current trend in spending more time at home continues, the focus should be on energy efficiency improvements in ICT technologies (television, computers, servers) and infrastructure that supports in-home activities. For example, improving the efficiency of online shopping supply chains such as warehouses and commercial transportation. 2) Development of personalized energy efficiency plans. Billions of dollars are invested as rebates every year in local and national level energy efficiency programs. The programs follow a blanket approach to target consumers. Given large heterogeneity in lifestyle, energy efficiency programs could benefit from a targeted approach, where consumers with higher energy savings potential are targeted. The idea of personalized energy efficiency plan is explored in depth in the third and fourth chapter.

The third chapter quantifies the effects of consumer heterogeneity on existing energy efficiency programs, through a case study on clothes washer, dryer, and television. Variability in metrics such as monetary benefits to the consumer and average cost of realized energy and carbon reduction (abatement cost) were calculated for buying an Energy Star certified device instead of a baseline technology using current rebate levels for the devices.

Large variability in monetary benefits and abatement costs was observed. Most households received a net economic benefit from more efficient appliances, although 5-7% do not save money from efficient washers or dryers and 12-20% save more than twice the savings of an average household. For a large percentage of households, abatement cost of electricity and carbon were higher than electricity price ($0.13/kWh) and social cost of carbon ($48/tC), in other words, the rebates were not cost effective. Further, behavioral heterogeneity (how a device was used) was larger than geographical variation in electricity prices and carbon emission factor of the electric grid. When comparing the products against each other, clothes dryers have the least abatement cost with a significantly larger population (90% and 41%) saving electricity and carbon at costs less than current electricity prices and social carbon cost, respectively.

Households that save the most energy also have the least abatement cost and are a potential target for utility rebate programs. Segments based on demographics are good identifiers of
potential target groups. Target demographics for washer and dryer (>10 loads per week) have an average of more than four members in their household with at least two children. Close to half of the households in this group earn more than $75,000 per year (100% employed). The target demographics for televisions (>6.6 hours per day) are older, less educated, without employment and earns less money.

The large variability suggests that program managers must include consumer information in designing energy efficiency programs. Program evaluators also benefit from collecting demographic information of consumers obtaining rebate to accurately measure program effectiveness.

The results described in chapter 3 are limited to the selected appliances. Smart meters and data mining techniques provide exciting opportunities in this area of research. For example, ability to disaggregate load profile of all appliances in a household allows for personalized energy plan for each household. Load profiles also provide additional information such as peak hours usage which are important in accurately measuring benefits and costs. Although smart meter data for large samples of population are not publicly available datasets such as American Time Use Survey (ATUS) can be leveraged to simulate the challenges and benefits from the future of smart meter data. ATUS records start and end time of activities performed by representative U.S. sample during a day which can be used to simulate daily patterns of various activities.

In chapter 4, ATUS was used to understand heterogeneity of television usage in the U.S. and identify consumer groups based on machine learning. Machine learning allows to segment consumers based on similarity of an individual’s television watching pattern. Consumer segments identified by their load profile were used to quantify energy savings and abatement cost.

Three distinct consumer segments were identified. As expected large heterogeneity was observed in television watching. Heavy television users spent 7.7 hours per day watching TV and represent only 14% of total U.S. population and consuming 34% of total television energy. Marginal energy savings potential from targeting one individual in heavy use segment is 7.1
times and 2.2 times greater than targeting an individual in low and medium use segment respectively.

Further energy savings from heavy usage segment could also reduce peak demand. Assuming 14% of Pacific Gas & Electric (PG&E) consumers exhibited TV watching pattern of the heavy use consumer segment, and they hypothetically adopt an efficient TV. PG&E could save $2-3 million annually from a reduction in energy demand as compared to 14% of the consumers exhibiting the average watching pattern. Translating to utility willingness to pay of $21 to $33 per customer for preferential adoption. The population of the heavy usage cluster in the U.S. tends to be older, less employed and less educated. These results echo major conclusions from chapter 3 regarding the benefits of targeting heavy energy users as compared to blanket programs. Also, the results elicit the benefit of daily usage pattern.

Looking forward, utilities must incorporate behavioral information in designing energy efficiency programs. Datasets used for the analysis may not represent the population served by the utilities. They also have several limitations such as accuracy, not comprehensive and outdated data. Following are methods, ranked in increasing cost and accuracy, that utilities may use to provide a personalized energy plan. 1) Conduct own survey of appliance use, 2) temporary smart meters combined with surveys and 3) permanent smart meters combined with disaggregation algorithms. Two strategies are suggested for utilities to target distinguished consumers groups: tiered communication and variable rebates. Tiered communication is the use of varying types of information to communicate the programs. Target segments may receive a phone call rather than a flyer. With Variable rebates, utilities would offer higher rebates to high-use customers or even limit program participation based on demographic characteristics.

Energy efficiency programs are funded by consumers. Therefore, like any public policy, energy efficiency programs are expected to be efficient and equitable. The argument in chapter 3 and 4 for targeting consumers with heavy energy use was based on economic efficiency. However, social impact of such policy needs to be discussed. Heavy energy use consumers for washer and dryer are demographic with higher income. One can argue that wealthy households should not receive rebates since they could afford an energy efficient device. In the flip side, incentivizing
wealth, heavy energy users could reduce strain on the grid and maintain lower energy prices. Incentivizing unemployed population to buy efficient TV raises moral questions.

Utility managers are tasked with designing a portfolio of programs that are both cost-effective and equitable. Equity of appliance rebate programs is unknown since they follow a blanket approach. By designing programs based on target groups utility managers can balance their portfolio by adding unassessed demographic groups.
References


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