Energy Policy 125 (2019) 537–547

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

How behavioral and geographic heterogeneity affects economic and environmental benefits of efficient appliances

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ARTICLE INFO

Keywords:
ENERGY STAR
Rebates
Efficiency program
Policy
Heterogeneity
Behavior

ABSTRACT

The economic and environmental benefits of efficiency are typically assessed assuming that all consumers use appliances in the same way. There are, however, significant differences in consumer usage patterns, as well as geographical variability in prices and environmental impacts of electricity. To explore the importance of heterogeneity, we first develop distributions of consumer-by-consumer economic benefits from purchasing an efficient versus standard appliance for televisions, clothes washers, and dryers in the U.S. We find large variability, e.g. for washers and dryers, 9% and 7.5% of the U.S. population do not save money over the lifetime of an efficient device, while 11% and 17% save more than twice that of an average consumer. Providing personalized savings information can thus inform and better motivate those consumers who would save more. Abatement costs for carbon and electricity use are similarly heterogenous as consumer economic benefits, indicating that adoption by heavy users is in the public as well as private interest. The cost of abating carbon via a utility appliance rebate program varies greatly by consumer. To scope the emission benefits of targeted adoption, we find that adoption by heavy users saves around 3 times more carbon than an average user for 10% participation in an efficiency program.

1. Introduction

Residential energy efficiency has the potential to realize significant energy and economic benefits. National potential of energy savings from residential efficiency programs is estimated to be 345 TWh per year, equivalent to 6.3% of the 2014 total U.S. electricity consumption (Wilson et al., 2017). Many energy efficiency upgrades, while costing more initially, are expected to deliver economic benefits over time from annual savings (Wilson et al., 2017). In the U.S. there are many government-driven policies and information programs to improve efficiency, including state and utility rebates, tax credits, Federal Trade Commission (FTC) labels, and utility information programs (Barbose, 2014; CEE, 2015; Shah and Phadke, 2011).

Heterogeneity in usage patterns and location could lead to large deviations in the benefits and costs of energy technologies from that of an average consumer. Usage patterns vary significantly by consumer, as illustrated in our work on television watching patterns (Sekar et al., 2016). Using cluster analysis to bin consumers into three distinct usage groups, we found that 15% of the population watches TV 7.7 h per day, 35% for 3 h per day, and 50% for 1 h per day. A consumer in the first group buying an efficient television saves over seven times more energy than one from the third group.

In addition to heterogeneity in usage patterns, the economic and environmental benefits of efficiency also vary geographically. A consumer living in a state with expensive and carbon-intensive electricity will save money and reduce carbon emissions more than a consumer in an average state. For example, for a given usage pattern, a consumer living in Pennsylvania will save 1.5 times more on their electricity bill and abate 4.4 times more carbon than someone living in Washington State.

Understanding usage and geographic variability has the potential to realize more effective interventions to improve energy efficiency. We discuss three applications. One use is to inform consumers: if homeowners received more personalized information on energy savings from an efficient option, those using more energy would recognize a larger economic benefit and presumably be more motivated to purchase.

The second use of improved information about heterogeneity is to inform rebate programs. At the state level, utility commissions are the main actors that promote energy efficiency as a public good. This is done through mandating and approving budgets for utilities to run efficiency programs. A primary mechanism in such utility efficiency programs is rebates on efficient appliances. Current rebate programs generally offer the same level of rebate to all customers. However, heavy users of an appliance will realize larger savings. If the rebate

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https://doi.org/10.1016/j.enpol.2018.10.035
Received 7 June 2018; Received in revised form 17 October 2018; Accepted 20 October 2018
Available online 20 December 2018
0301-4215/

preferentially encourages these consumers to upgrade, larger energy savings could be achieved with lower expenditures. Rebate programs could be targeted, in quantity of subsidy or advertising efforts, to subgroups that would save more from the upgrade. Utility regulators and ratepayer advocates often worry that targeted rebate programs could lead to equity issues, i.e., rebates going to primarily high-income ratepayers (Borenstein and Davis, 2016; Frank and Nowak, 2016; Neveu and Sherlock, 2016). Therefore, it is also important to consider the distributional equity of rebates.

The third use of resolving heterogeneity is in development of policy tools such as marginal abatement cost curves (MACC). MACC are useful for policy makers as they provide a rank order of the carbon mitigation measures based on their abatement cost along with the potential emission reduction. Prior MACCs, such as those developed by McKinsey, do not resolve for usage and geographic heterogeneity (Nauclér and Enkvist, 2009).

Historically, energy efficiency analyses and programs typically treat consumers as a representative average. Some examples include: 1) measurement and verification of utility efficiency programs depend on expected (or deemed) energy savings, an a-priori estimate of energy savings for an efficiency measure (State and Local Energy Efficiency Action Network, 2012), 2) the Federal Trade Commission (FTC) labels show energy and economic savings for national average usage patterns and electricity prices (FTC, 2015), and 3) use of blanket approaches (billboard ads, mass media, mass mailing) to market energy efficiency programs. Utilities are beginning to use attitude-based consumer segmentation methods to improve participation in efficiency programs (Frankel et al., 2013; Van de Grift et al., 2014). While this method may lead to improved participation, it does not necessarily optimize for increasing energy savings which is the objective of most utility energy efficiency programs. For example, investor-owned utilities in Texas are mandated to reduce 30% of annual demand growth through energy efficiency programs (Frontier Associates LLC, 2016).

Despite the dependence of energy efficiency benefits on behavioral and geographical heterogeneities, they are infrequently studied, with more analysis of geographical heterogeneity. Cai et al. (2013) and Diamond (2009) studied the effects of geographical variations in prices and energy use heterogeneities on the adoption of hybrid electric vehicles and residential solar photovoltaics (PV) respectively. They noted that, as expected, adoption rates are larger among consumers experiencing higher fuel price and energy use. Chini et al. (2016) addressed the regional differences in abatement cost curves of various household appliances. Numerous studies analyzing heterogeneity in emission intensity have recommended 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).

Allcott et al. (2015) showed that blanket programs, in theory, can be inefficient and suggests tagging and targeting populations to increase welfare gains from energy efficiency programs. Carrie Armel et al. (2013) suggest that smart meter data with disaggregation algorithms can be leveraged to provide household-specific information on energy consumption for each device, which could inform customized energy efficiency programs. There is as yet no analysis that, for a large cohort of homes, builds up residential energy consumption as a function of individual household usage patterns and location, showing how each factor contributes to a distribution of energy use and benefits of efficient technologies.

To address this gap, we undertake analysis to characterize the heterogeneity of benefits and costs for the purchase of three efficient household appliances in the U.S.: clothes washers, clothes dryers, and televisions. We use micro-data from the Residential Energy Consumption Survey (RECS) (EIA, 2012) to describe usage and geographic heterogeneities, estimating each consumer's energy savings, net present value of investment, carbon reductions, and carbon abatement cost.

These three products were chosen for three reasons. First, they account for a substantial 14% of electricity consumed in U.S. households. In a typical U.S. home in 2014, the share of total electricity consumption for clothes washer, dryers and televisions were 3%, 5%, and 6% respectively. Second, as will be seen in the analysis, all three products have large heterogeneity in usage patterns. Third, all three products are commonly covered in utility rebate programs: there were approximately 175 programs around the country offering rebates for efficient TVs, washers, or dryers. Typical rebates for an ENERGY STAR certified television, washer, and dryer are $25, $50 and $50 respectively (EPA, 2016a). We assess purchase of an ENERGY STAR certified appliance compared to a standard (and less expensive) alternative.

We use the results on usage and geographic heterogeneity to inform the design of residential rebate programs, and we are the first to provide this empirical analysis of the effects of heterogeneity on rebate programs. There have been several calls to better target efficiency policies towards sub-groups of consumers that would save the most from adoption (Allcott et al., 2015; Borgeson, 2013; Carrie Armel et al., 2013; Sekar et al., 2016). What we contribute to this discussion is specific quantitative results on what groups would benefit from an efficient appliance and to quantify those benefits.

2. Methods and data

To understand the impact of behavioral and geographic heterogeneity on the adoption of ENERGY STAR certified televisions, clothes washers, and dryers, we calculate the variability in consumer's energy savings, net present value of investment, carbon reductions, and carbon abatement cost for various households. The metrics are calculated by comparing the energy and price difference between the respective product that just qualifies under federal standards (the baseline) and ENERGY STAR standards (efficient). To assess the cost-effectiveness of the rebate program, abatement cost of electricity and carbon are calculated and compared with respective benchmarks: the cost of electricity production and the social cost of carbon. The rationale for this comparison is rooted in the environmental economics argument that to justify the use of public funds (or state-mandated utility funds), public benefits (reduced environmental damage) must be less than the financial cost of a program (rebate expenditures). The effects of behavioral and geographic heterogeneity are also studied independently from each other to gauge their influence on the distribution of the various metrics measured. Finally, the demographics of high-energy use and -carbon emitting consumers are determined.

The American Time Use Survey (ATUS) (BLS, 2015) and Residential Energy Consumption Survey (RECS) (EIA, 2012) provide the user behavior, geographic, and demographic information for the three products. State-level energy prices and emission factors are obtained from EIA databases. Energy, carbon savings, and price differences from purchasing ENERGY STAR certified equipment are obtained from the respective ENERGY STAR technical documentation.

2.1. Modeling energy consumption, water use, and cost of ENERGY STAR versus standard appliances

The effects of consumer heterogeneity are calculated by comparing a standard ENERGY STAR product versus a baseline (non-ENERGY STAR) available in the market. Specifications for ENERGY STAR and baseline versions, such as energy use, water use, and incremental price are obtained from the ENERGY STAR technical reference manual and personal communications (DOE, 2012a, 2012b; EPA, 2016b, 2015a, 2015b; Vokes, Personal communication). The energy modeling is summarized in this section, detailed formulae and data sources are in the Supporting information.

The specifications for clothes washers vary depending on their technology type and size. Front-loading washers are more energy and water-efficient than top-loading but cost more. An ENERGY STAR clothes washer saves both energy and water.

The electricity savings of energy efficient washer and dryer is described by Eq. (1):

$$\textit{Annual Savings (kWh)} = \Delta C \times n\left(\frac{loads}{week}\right) \times 52\ (weeks) \tag{1}$$

where ΔC is the energy difference between efficient and non-efficient models and n is the number of loads per week, which varies by household. For this paper, energy savings and water savings from a 4.5 ft^3 ENERGY STAR washer are compared to federal standards using their respective factors. It must be noted that 80% of total energy per wash is thought to be used in heating water, while the remaining 20% for electricity to run the washer (EPA, 2016b). Energy difference is calculated based on rated unit electricity consumption of washers with an electric water heater. In the case of homes with gas water heaters, an energy factor of 75% is used to convert the rated unit electricity consumption of a clothes washer with electric water heater to gas water heating system (10 CFR Appendix J2 to Subpart B of Part 430). The incremental cost of ENERGY STAR washers - the difference between ENERGY STAR and baseline models - is $190 for top-loading and $50 for front-loading washers (EPA, 2016b).

Clothes dryer calculations are similar to those for washers. We analyze both electric and gas dryers, considering only vented dryers, the most common type. The energy usage of clothes dryers is indicated by the combined energy factor (CEF), which is the ratio of the load size and the energy use during operation. We assume the capacity of dryers to be 5 ft^3 and load size of 3.83 kg per wash. The CEF for dryers of capacity 4.4 ft^3 or more from (EPA, 2016b) was used for energy savings calculations. The incremental cost of sales-weighted ENERGY STAR versus base versions was $75 and $40 for electric and gas dryers, respectively (EPA, 2016b). Note that there is an interaction between energy use of washer and dryer due to the degree to which the washer's spin cycles removes water. We neglect this interaction in our analysis. Table 1 shows summary data used in estimating energy use of efficient televisions, clothes washers and dryers.

In the case of televisions, the sales-weighted average ENERGY STAR device consumes 81 kWh/year while a non-ENERGY STAR product consumes 112 kWh/year (EPA, 2016b). The size segment of the representative TV is a 50″ LCD. ENERGY STAR assumes an average TV usage of 5 h per day to calculate the total energy consumption. According to ENERGY STAR and Itron (Itron, Inc, 2014; Vokes, Personal communication), 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 17 W during operation. The power difference between the ENERGY STAR and baseline product during standby mode is considered insignificant since the power draw during standby mode was already less than 1 W for all devices. The energy savings are calculated as the product of power and hours of television usage given by Eq. (2):

$$\textit{Annual Savings (kWh)} = \Delta C \times n\left(\frac{hours}{week}\right) \times 52\ (weeks) \tag{2}$$

A sample calculation of energy and water savings for each device is shown in the Supporting Information. Rebates are used in analyzing net benefits of utility efficiency programs.

The EPA ENERGY STAR program publishes a summary of all utility efficiency rebates available across the country (EPA, 2016a). There were only 4 television rebate programs identified, with rebates varying from $25 to $150. For washing machines, there are 105 programs with rebates varying between $20 and $235, while for clothes dryers there are 65 programs with rebates varying between $25 and $300. A typical rebate for clothes washer and dryer is around $50 each.

2.2. Microdata on consumer behavior

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 provides 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 factors are identified and linked to each respondent.

ATUS is an annual survey conducted by the U.S. 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 with 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 the 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, 2015).

RECS is conducted once every few years by the US Energy Information Agency (EIA). The latest RECS was conducted for the year 2015. 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.

2.3. Behavioral heterogeneity for televisions, clothes washers and dryers

Fig. 1 shows the heterogeneity in television watching patterns and

Table 1

List of figures used in calculating savings from purchasing ENERGY STAR (ES) versus baseline versions of televisions, clothes washers, and dryers. For simplicity we show all natural gas savings as kWh by using the conversion factor, 1 therm = 29.3 kWh. To disaggregate natural gas savings from machine electrical energy, readers should refer to the supporting information (SI).

Sources: Television behavioral use: ATUS (BLS, 2015); Washer and Dryer use characteristics: RECS (EIA, 2012); all other data are obtained from ENERGY STAR (EPA (2016a, 2016b).

End use technology	Behavior	Appliance characteristics	Incremental cost	Rated electricity savings ΔC	Utility rebates
Television	Time spent (hours/week)	50″ LCD, 7 years lifetime	$0	0.017 kWh/h	4 programs $25–150
Clothes Washer	No. of loads/week	4.5 ft^3 top-loading, 11 years lifetime 4.5 ft^3 front-loading, 11 years lifetime	$190 $50	0.4 kWh/load 0.1 kWh/load	105 programs $20–235
Clothes Dryer	No. of loads/week	5 ft^3, Electric, 12 years lifetime, 3.83 kg of clothes per load 5 ft^3, Natural gas, 12 years lifetime, 3.83 kg of clothes per load	$75 $40	0.6 kWh/load 0.55 kWh/load	65 programs $25–300

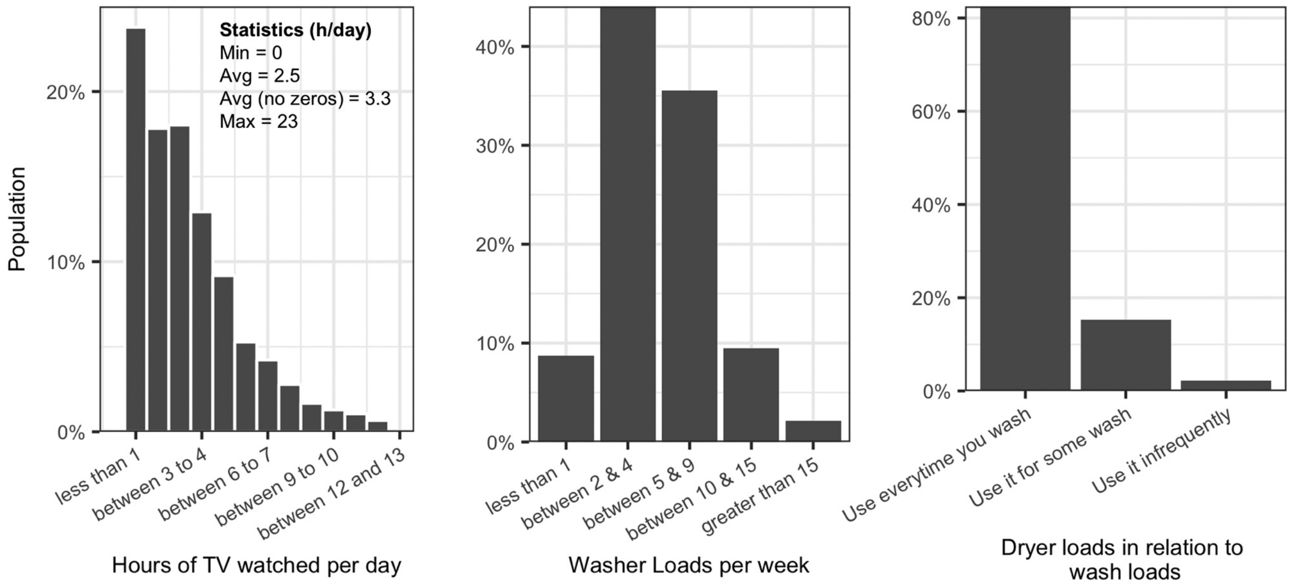

Fig. 1. Heterogeneity in the usage of televisions, clothes washer and dryers. Note, the x-axis for television behavior is truncated for presentation.

Table 2
Average, minimum, and maximum of state average prices of electricity, natural gas, water, and carbon emission factors in the U.S.
Sources: (EIA, 2015; EPA 2017, 2016b).

Item	Units	Min	Median	Max
2015 Electricity Price	cents/kWh	9.76	12.1	19.8
2015 Natural gas Price	$/therm	0.79	1.1	1.95
Water Price	$/1000 gallons	10.5		
2014 Electricity Carbon Emission Factor	kg/MWh	202	510	820
Natural gas Carbon Emission Factor	kg/therm	5.31		

frequency of washing and drying loads in the U.S. The data for televisions represent the year 2015 usage patterns for a representative population in the U.S. (BLS, 2015). Washer and dryer loads represent households in the U.S for the year 2009 (EIA, 2012). At the time of writing, new RECS data was unavailable and 2009 usage data is assumed to hold true for current laundry patterns.

Around 22% of the surveyed population reported not watching television at all on the day surveyed. The average television watching time in the U.S. is 2.5 h per day. When excluding the population that did not watch TV that day, the average watching time increases to 3.25 h per day. There is large variability in TV use, with about 20% of watchers viewing more than 5 h per day.

In the case of washers, 50% of households do 2–4 loads per week, followed closely by 35% households that do 5–9 loads per week. 80% of the people report using the dryer for every use of 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 load per week to more than 15 loads per week). Unlike the data on television usage, frequency of washers and dryer usage was collected as "binned" data, and we use mean values of each bin. For the extreme values (less than or equal to 1 and 15 or more loads per week) values of 1 and 15 were assumed. The uncertainty arising from this assumption is discussed later in the paper. Unlike washers, only qualitative data is available for dryers, with 80% using dryers everytime they wash while the remaining use it for some wash or infrequently. Therefore, we have assumed that dryer usage follows the clothes washer.

RECS also provide the technology type for each device. 81% of households have top-loading washing machines. 50% of households use electricity for water heating and another 47% used natural gas. 3% of households use propane and heating oil as fuel for heating water. For those cases, natural gas emission factors and prices are used for simplicity. 80% of households have an electric dryer, the rest use natural gas dryers. Note that RECS only polls households with individually owned appliances and household payment of utility bills. There are rental units in which one or both of these conditions do not hold - these are not included in our analysis.

2.4. Geographical heterogeneity in energy prices, water prices, and emission factors

Electricity, natural gas, and water prices vary by location, as does the carbon intensity of electricity. This variability influences the economic and carbon benefits of efficient appliances. Table 2 summarizes the geographic heterogeneity of prices and emission factors. While we aim to characterize geographical heterogeneity, our treatment is limited by the public reporting of RECS results. While EIA queries individual addresses of respondents in RECS, reported locations are aggregated to 27 EIA-defined state-groupings (EIA, 2012). We thus do all analysis using the EIA state-groupings. Economic costs of electricity and natural gas consumption are calculated by using state-group average prices. Similarly, carbon emissions due to the electricity use by the appliances are estimated using state-group level average emissions factors. See the supporting information for detailed price and emission factor data for states and state-groups.

We have used the average state-level carbon emission factors provided by eGRID (EPA, 2017). The emission factor does not consider any electricity trade between eGRID subregions. Despite this shortcoming, eGRID is considered the best proxy for state-level average emission factors available. Marginal emissions factors are another option, better reflecting near-term adoption for small changes in demand (low adoption). We use average emissions factor in the main text, but present results using the EPA's non-baseload time independent marginal factors in the Supplemental information. The carbon (CO_{2eq}) emissions factor for natural gas is 5.31 kg/therm (EPA, 2018). The emission factors do not include emissions associated with the lifecycle of energy production, i.e., the production, transportation, and disposal of the fuel and raw material associated with the energy production.

The median electricity price, natural gas price, and carbon emission factor for electricity are 12.1 cents/kWh, $1.1/therm and 510 kg/MWh, respectively. Electricity prices in the EIA state-groups vary between 80% and 163% of the median, while emissions factors vary between

39% and 160% of the median. Natural gas prices range from 72% to 170% of the median. Note that variability in electricity prices and emission factors are smaller than variability due to behavior. For example, from Fig. 1, the energy use of clothes washer can vary by more than a factor of 15 depending on household usage.

Efficient clothes washers gain significant water savings relative to their baseline. For this reason, we include the economic benefit from water savings. However, location-specific water prices are not easily available, so a constant value of $10.5 per 1000 gallons (including sewer rates) is assumed (EPA, 2016b).

2.5. Formulation of economic and energy metrics

We use several metrics to assess the benefits of efficient appliances, including energy savings (annual kWh), Net Present Value ($), carbon abated (ton CO_{2eq}), and carbon abatement costs ($/ton CO_{2eq}).

Net Present Value (NPV) is the sum of the incremental capital cost and discounted monetary benefit from purchasing the ENERGY STAR technology. Television and clothes dryers only have energy savings while washers save energy and water. Eq. (3) expresses NPV in mathematical form. We also use Equivalent Annual Cost (EAC) to describe the monetary benefits. EAC is the annual cost of owning and operating the technology over its lifetime. Eq. (4) shows the formula to calculate EAC from NPV.

The Net Present Value (NPV) (in $) is

$$NPV_{T,i} = -IC_T + \sum_{y=1}^{n_T} \frac{\Delta Q_{T,i}^{elec} \times \Delta P_i^{elec} + \Delta Q_{T,i}^{gas} \times \Delta P_i^{gas} + \Delta Q_{T,i}^{water} \times \Delta P_i^{water}}{(1+r)^y} \tag{3}$$

The Equivalent Annual Cost (EAC) (in $/yr) is

$$EAC_{T,i} = \frac{NPV_{T,i} \times r}{1 - \frac{1}{(1+r)^t}} \tag{4}$$

$NPV_{T,i}$ is the Net Present Value from purchasing end use technology T for each person or household i. $\Delta Q_{T,i}^{elec}$, $\Delta Q_{T,i}^{gas}$, $and \Delta Q_{T,i}^{water}$ are annual quantities of electricity, heat, and water savings from technology T for each person or household i respectively. Energy and water savings are calculated based on the formula used in Eqs. (1) and (2). We assume that households do not switch technology type: i.e., a household with a front-loading washer continues to choose the same technology type. P_i^{elec}, P_i^{gas}, $and\ P_i^{water}$ are residential prices for electricity, natural gas, and water for each household i respectively. r is the discount rate, set at 5%, and y is an index for *year* and it varies between 1 and n_T (average lifespan of technology). IC_T is the incremental cost of buying an ENERGY STAR product compared to its baseline.

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. Eq. (5) summarizes the carbon reduction associated with adopting a technology T for each household i.

$$Carbon\ Abated_{T,i} = \Delta Q_{T,i}^{elec} \times EF_i^{elec} + \Delta Q_{T,i}^{gas} \times EF_i^{gas} \tag{5}$$

$EF_i^{elec}\ and\ EF_i^{gas}$ are the emission factors for electricity and natural gas for each person or household i.

The abatement cost of carbon is the ratio of net cost of adopting a technology and the amount of carbon saved. We separately calculate abatement cost of carbon from consumer and utility perspetive. For consumers, the cost of adopting the technology is equal to the negative of the net present value calculated above. In the case of utilities, the cost is the rebate paid to the consumer (plus overhead expenses). For simplicity, we do not include the overhead costs of running an efficiency program or other indirect benefits of demand reduction. As rebate programs are focused on saving energy (with the co-benefit of reducing carbon), the abatement cost of electricity savings is also measured as the ratio of rebate and total electricity saved. Equations (6-8) show equations for Consumer Carbon Abatement Cost, Utility Carbon Abatement Cost, and Utility Electricity Abatement Cost.

$$\text{Consumer Carbon Abatement Cost}_{T,i}\left(\frac{\$}{tCO_{2eq}}\right) = \frac{-NPV_{T,i}}{Carbon\ abated_{T,i}} \tag{6}$$

$$\text{Utility Carbon Abatement Cost}_{T,i}\left(\frac{\$}{tCO_{2eq}}\right) = \frac{rebate_T}{Carbon\ Abated_{T,i}} \tag{7}$$

$$\text{Utility Electricity Abatement Cost}_{T,i}\left(\frac{\$}{kWh}\right) = \frac{rebate_T}{Electricity\ savings_{T,i}} \tag{8}$$

Where $rebate_T$ is the rebate amount in $ for each technology T, the same for all consumers.

3. Results and discussion

Based on the methods described, four results are presented and discussed in this section. First, we show variability in consumer-centered metrics: energy and carbon savings, NPV and consumer abatement costs. Second, utility abatement costs for electricity and carbon are shown. In addition, to illustrate public and utility benefits of adoption, we calculate the percentage of population with abatement costs for carbon and electricity less than the social cost of carbon and electricity price. Third, critical sub-populations that save more energy than others are identified and their demographics characterized. Lastly, the effects of behavior and geographic heterogeneity are separated and compared with the case accounting for both heterogeneities.

3.1. Heterogeneity in energy savings and economics

Fig. 2 shows histograms for energy savings and net present value of purchasing an energy efficient appliance. Significant heterogeneity is observed across all the metrics measured.

3.1.1. Televisions

Large variations in behavior for televisions were observed, with min and max of 0.02 and 23.8 h per day of television watching, respectively. We include only behavior between the 10th and 90th percentile to avoid outliers. The 10th and 90th percentile values are 0.8 h and 7 h respectively. The median lifetime energy savings of an efficient television is 110 kWh with a monetary benefit of $12, the lowest of the examined devices.

3.1.2. Clothes washers

The weighted median energy savings from households buying clothes washers was 60 kWh/year, corresponding to an average of 5.6 loads per week. The minimum and maximum energy savings are 5.5 and 200 kWh/year for households with lowest and highest bins of loads per week. The equivalent annualized cost (assuming 5% discount rate) of purchasing an efficient clothes washer varies between -$12/yr and $188/yr, with a median of $15/yr. 9% of the households have a negative NPV while 11% have NPV greater than $615, double the average savings and 38% have NPV greater than $250, more than double the median savings.

For clothes washers, water savings provide an additional monetary benefit to the consumer. The monetary benefits from water savings are substantially higher than electricity bill savings, contributing 70–90% of monetary benefit. The median water savings is 2900 gallons per year, with a minimum and a maximum of 234 and 14,400 gallons per year respectively. The monetary savings translates to $30 per year in median with minimum and maximum of $2.5 and $150 per year.

3.1.3. Clothes dryers

Dryers have the largest energy savings of the three technologies

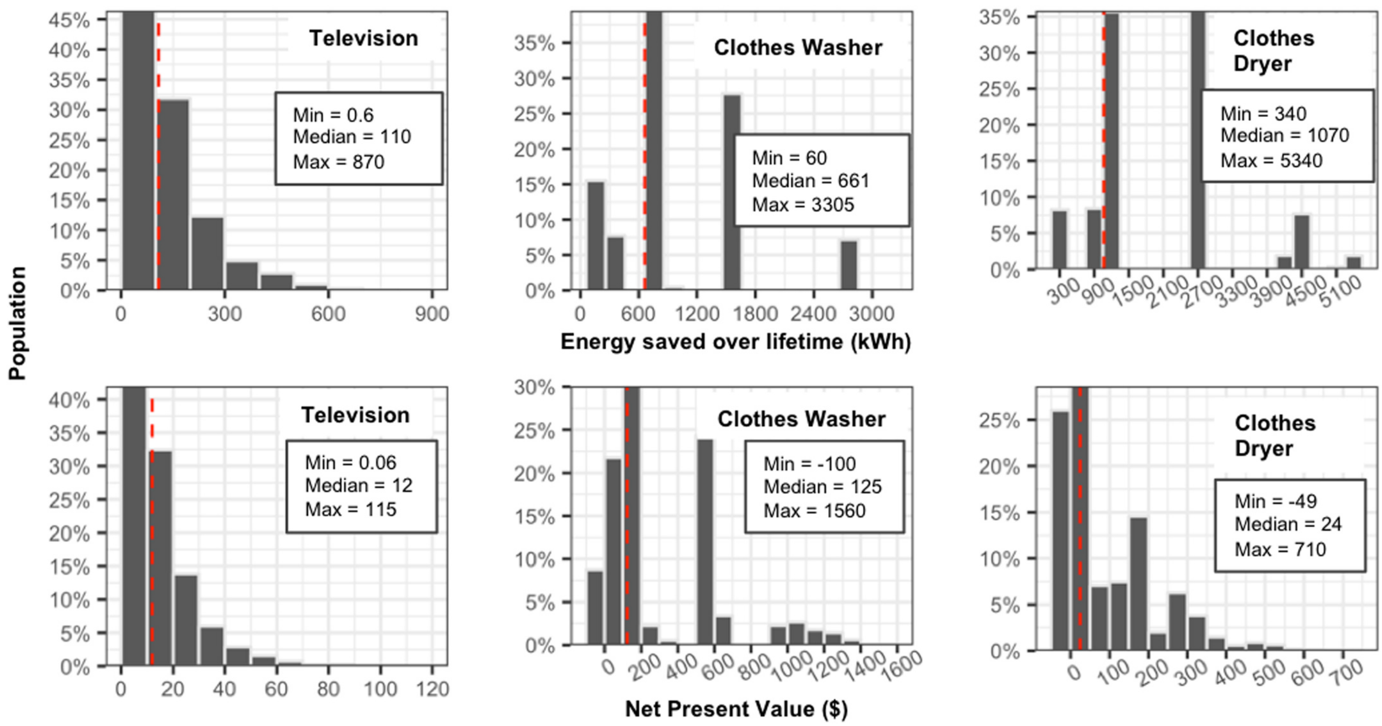

Fig. 2. Histograms for Energy Savings and Net Present Value of purchasing an efficient television, clothes washer, and dryer. Net Present Value is calculated with a non-subsidized price of an efficient appliance, the consumer's savings on utility bills and prices reflecting the location of the household. The red dashed line indicates the median.

evaluated. The median energy savings is almost one order of magnitude higher than televisions and about twice that of washers. The median energy savings from dryers is 90 kWh/year with minimum of 28 kWh/year and maximum of 445 kWh/year. A longer lifespan for dryers compared to TVs and washers (12 years versus 7 and 11 years) contributes to larger lifetime energy savings (EPA, 2016b). Recall from section 2.3 that RECS does not query dryer loads per week as done for clothes washers.

We therefore assumed the number of dryer loads per week to be the same as washers (refer: Fig. 1). Note however that around 80% of the population report that they use the dryer every time they wash. The rest "use it for some wash" and "infrequently". Our assumption of 1 washer load = 1 dryer load overestimates dryer usage for ~20% of the population.

The Equivalent Annual Cost of purchasing an efficient dryer varies between -$6 and $80 per year by consumer. Despite their larger energy savings and longer expected lifetime, the total monetary benefit from dryers are lower than washers because efficient washers benefit from both energy and water savings. 7.5% of the residents do not recover their cost of investment. The average savings is $90 over the dryer's lifetime, 17% of consumers save more than double this. While 45% save more than double the median savings of $24.

Energy savings and NPV from Fig. 2 combine both electric and gas dryers. Results for the two types actually differ because electric dryers save slightly more energy and gas is a less expensive fuel compared to electricity. With the same usage behavior, switching from baseline to ENERGY STAR gas dryer saves 0.55 kWh/load, while switching for an electric dryer saves 0.6 kWh/load. The median of gas and electric dryer energy savings over their lifetime are 86 and 89 kWh. Heat savings in *therms* are converted to kWh using the conversion factor 1kWh = 0.0341 therm. For monetary benefits, the NPV of switching to an efficient gas dryer is negative except for < 1% of users with positive (but small) NPV ($2-$5), with a median for all users of -$31. In contrast, 92% of electric dryer users have positive NPV for switching, with a median for all users of $69.

3.2. Heterogeneity in carbon abatement and consumer carbon abatement cost

3.2.1. Televisions

The net carbon abated by an efficient television ranges from 0 to 0.6 t, with a median savings of 0.05 t over the lifetime. Net carbon reductions are modest compared to clothes washers and dryers due to the small difference in power consumption between ENERGY STAR and baseline models (17 W). Because the Net Present Value of efficient television is always positive (no difference in purchase cost), carbon mitigation costs are always negative, ranging from −116 to −748 $/tCO$_{2eq}$. The median is -$190/tCO$_{2eq}$.

3.2.2. Clothes washers

Total carbon abated over the lifetime (11 years) of clothes washers varies between 0.01 and 2.7 t of carbon. The range of carbon savings is larger than energy savings because of the additional heterogeneity due to geography (emission factors). Some consumers do not save money with an efficient washer, so the cost of carbon abatement is positive in those cases. This illustrates an important result that carbon abatement costs of efficiency can be positive or negative depending on behavior. As total carbon savings are less than 1 t per consumer, carbon abatement costs are large and have a wide range between −2280 and 1770 $/tCO$_{2eq}$. Embedded carbon emissions from water savings are not considered in this paper.

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, in some states, such as Idaho, Maine, New Hampshire, Oregon, Vermont, and Washington, the carbon intensity of electricity is lower than carbon intensity of natural gas (5300 gCO$_{2eq}$/therm or 180 kgCO$_{2eq}$/MWh). Second, electric water heaters are more efficient than gas ones, roughly 90% versus 60% efficient, respectively.

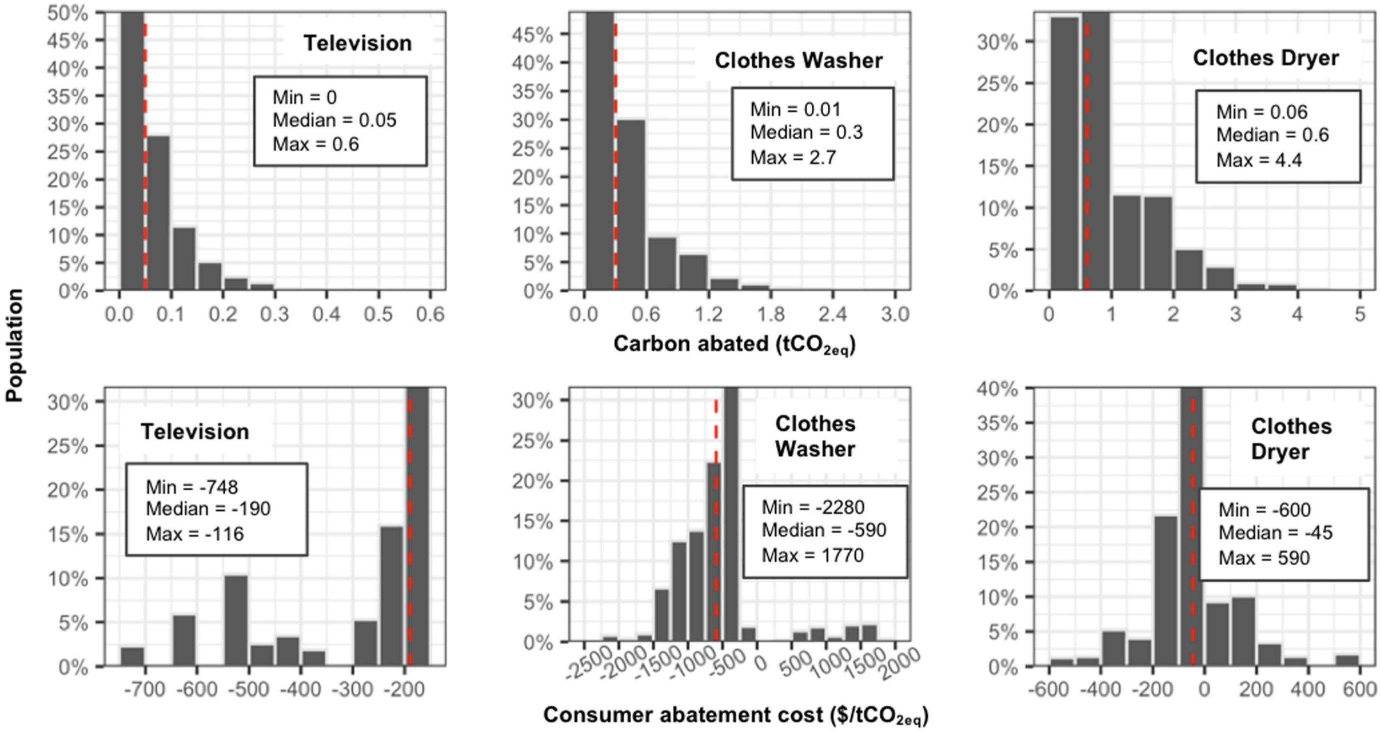

Fig. 3. Carbon abated over appliance lifetime (tonnes CO_{2eq}) and Consumer Carbon Abatement Cost ($/t$CO_{2eq}$) for an efficient television, clothes washer, and dryer. Consumer Carbon Aatement Cost is based on Net Present Value with non-subsidized prices of efficient appliances and the consumer's savings on utility bills. The red dashed line indicates the median.

3.2.3. Clothes dryers

Average carbon savings track energy savings. The large energy savings from efficient dryers leads to a median consumer-level carbon emissions reduction of 0.6 t, twice that of washers and televisions combined and resulting in consumer carbon abatement costs from –600 $/t$CO_{2eq}$ to 590 $/t$CO_{2eq}$, with a median of –$45/tCO_{2eq}. Due to the large range of carbon benefits and a smaller range of monetary benefits, the range of consumer carbon abatement costs are lower than for

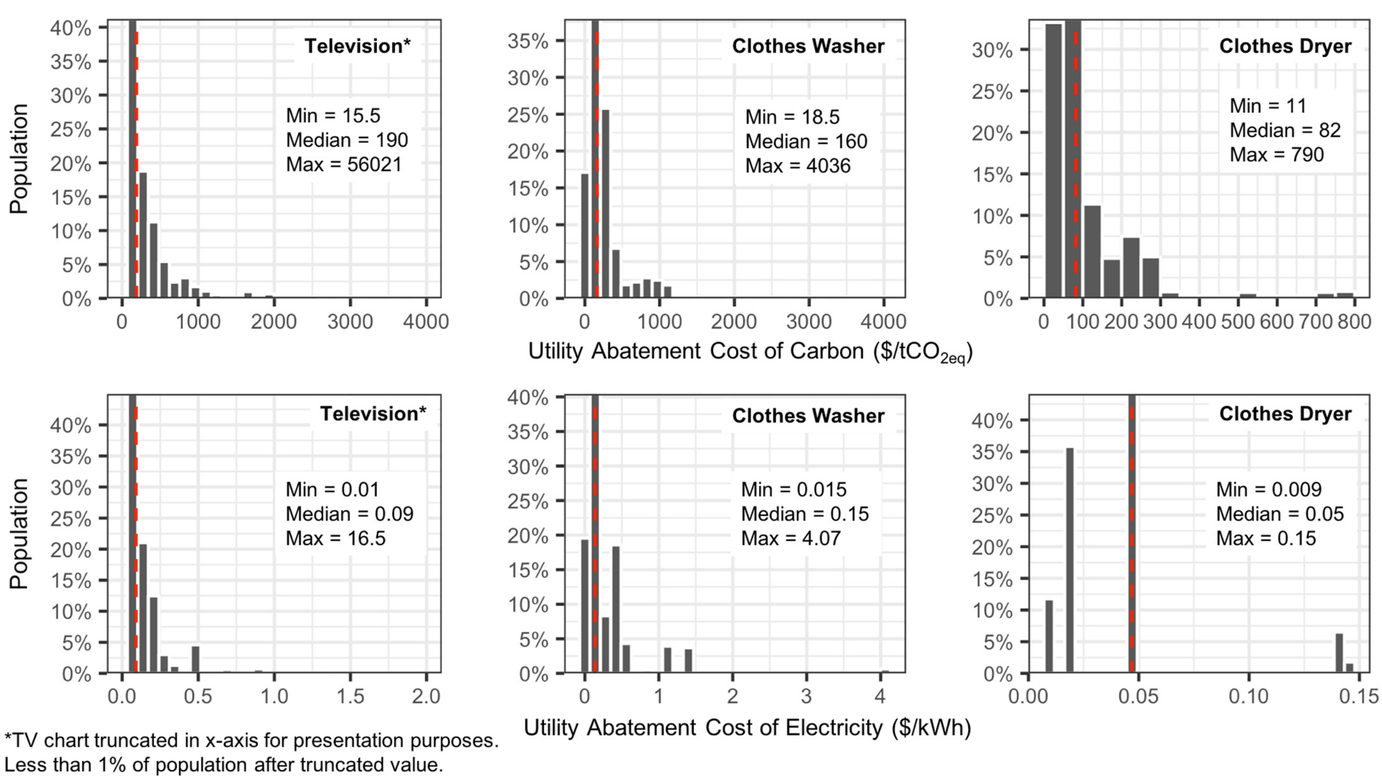

Fig. 4. Utility Carbon Abatement Cost (carbon reduced per rebate expenditure) and Utility Electricity Abatement Cost, measured in $/tonnes of carbon and $/kWh respectively. The red dashed line indicates the median.

washers.

Carbon abated and consumer abatement cost of electric and natural gas dryers are combined in the results shown in Fig. 3. Carbon savings for a gas dryer varies between 0.06 and 1.1 tCO_{2eq} with a median of 0.21 tCO_{2eq} and 0.07–4.4 tCO_{2eq} with median of 0.73 tCO_{2eq} for electric dryers. Consumer carbon abatement cost of gas dryers vary between –\$5.8 and \$590 per tonne of carbon with median of \$156 per tonne of carbon. In the case of electric dryers, the consumer carbon abatement cost vary between –\$600 and \$374 with median of –\$85 per tonne of carbon. A lower emission factor of natural gas explains the lower range of carbon savings from gas dryers. However, there are some states where the emission factors of electricity is lower than natural gas emission factor i.e., total carbon savings from natural gas dryer is higher than electric dryers.

3.3. Cost-effectiveness of rebates

To characterize the effect of heterogeneity on the effectiveness of rebates, we calculate the distribution of subsidy expenditure per unit of electricity savings and carbon reductions. Since the objective is to estimate the value of the rebates to the utility, consumer costs are not included. For carbon, we compare the cost of abatement (\$/tCO_{2eq}) via a subsidy with estimates of the social damages. For the latter, we use the mean estimate of \$48/ton (Interagency Working Group on Social Cost of Greenhouse Gases, US Government, 2013).

Fig. 4 shows the distributions for carbon and electricity demand abatement costs for utility rebate programs. The median carbon abatement costs for televisions, washers, and dryers is \$190/tCO_{2eq}, \$160/tCO_{2eq} and, \$82/tCO_{2eq}, respectively. All three mitigation costs are higher than a social cost of carbon of \$48/tCO_{2eq}, suggesting that the subsidy has poor justification solely as a carbon mitigation measure for an average consumer. Note, however, that there are consumers for all three groups with mitigation costs less than \$48/tCO_{2eq}. Washers and dryers that use natural gas have a much larger carbon abatement cost compared to an electric washer and dryer.

The median abatement costs of electricity for televisions and clothes washers are lower than the average retail electricity price of \$0.126/kWh, indicating that the average rebate is cost-effective for televisions and dryers, presuming the goal is to reduce consumption at a price lower than delivered electricity. Washer rebates are not cost effective. Instead of retail electricity prices, one could compare electricity abatement costs with the avoided cost of building a new power plant. Only dryers are cost effective when compared with the levelized cost electricity (LCOE) of a new natural gas power plant at \$0.07/kWh.

To clarify the size of the population for whom a subsidy results in comparatively inexpensive carbon or electricity savings, we determine the percentage of population that is cost-effective at various rebate levels, i.e. the mitigation cost is lower than the social cost of carbon or electricity price. Results are shown in Fig. 5. The figure shows that as the rebates increase, for carbon abatement the percentage of the population that is cost-effective decreases rapidly at the beginning and at a slower pace near the end. For electricity savings, televisions show a similar pattern while a large share of the population continues to be cost-effective even at larger rebate values.

At the default rebate levels of \$10 for televisions, \$50 for washers, and \$50 for dryers, less than 6%, 7%, and 33% of the population respectively have an abatement cost of carbon less than the social cost of carbon. At the same default rebate, 65% (televisions), 46% (washers), and 91% (dryers) of households save electricity at a price less than average retail electricity price of 12.6 cents/kWh. Note that the cost to the utility of an incentive has been assumed as the rebate received by consumers. There are other costs to utilities that are not included here such as program administration, overhead, evaluation, measurement, and verification costs. We do not include these costs because utilities report overall program costs with no breakdown by appliance. Inclusion of these costs would reduce cost-effectiveness. On average, program overhead costs are approximately 25% of total administration costs. With respect to benefits, we do not include avoided transmission and distribution costs because, on average, they account for a comparatively small share, 1–5%, of avoided capital cost of new capacity additions (EIA, 2018). Also, note that these calculations implicitly assume that the carbon and energy benefits of an efficient appliance are wholly attributable to the rebate program. In reality, some customers ("free riders") would adopt these appliances even without a rebate.

Non-utility system benefits and costs are not included in the study, some of these include public health benefits from avoided air pollutants other than carbon, energy security, economic development, and jobs. The metrics presented are from the utility and consumer perspective (as NPV). If non-utility system benefits and costs are added, the total societal benefits of rebates could be evaluated. All three perspectives, consumer, utillity and society, are useful to consider in designing a holistic policy. For example, Amoroso et al. (2018) calculated the benefit and costs of incentivizing consumers to size residential air conditioning systems from consumer, utilitiy, and societal perspectives. They provide policy guidance based on seeking win-win solutions for all three stakeholders.

3.4. Comparison of behavioral and geographic heterogeneity

All the results presented above combine both behavioral and geographic heterogeneity. Descriptive statistics of the usage patterns (Fig. 1), electricity prices, and emission factors (Table 2) suggest that behavioral heterogeneity is larger than geographic heterogeneity. To illustrate how different heterogeneities influence results, we isolate the effect of behavior and geographic heterogeneities for a targeted intervention that maximizes carbon savings compared to a blanket (random) program. First, we calculate the potential carbon savings for each household from the adoption of an efficient appliance under three scenarios: (i) include usage heterogeneity but assume a geographically average emission factor *(variable behavior, average location)*, (ii) include geographic heterogeneity but assume average usage *(variable location, average behavior)*, and (iii) include both heterogeneities *(variable location, variable behavior)*. Next, we calculate the potential benefit of a targeted intervention by finding carbon savings when the top carbon-saving population adopts and compare this with carbon savings under random targeting. This assumes that a targeted intervention is 100% successful in ensuring participation from top carbon-saving households – essentially forcing the efficiency upgrade on households in the order of their potential carbon abatement. While 100% success in targeting is not a practical goal, we use it to estimate the theoretical maximum of carbon savings.

Fig. 6 shows the percentage increase in carbon savings as a function of the percentage of population targeted for the three scenarios. The result shows that there is a large carbon savings potential when resolving for heterogeneity for these appliances. For example, successfully targeting the 10% of the population with the highest carbon savings leads to around 3 times more carbon savings compared to an average (random) 10% participation rate for all the three appliances. As the target population increases, the difference between targeted and random intervention decreases. Given low program participation rates of efficiency programs, considering heterogeneity is important.

The carbon savings curve for "*variable behavior, variable geography"* and "*variable behavior, average location"* scenarios run very close to each other suggesting that usage pattern largely drives the total heterogeneity of all three appliances. In other words, location heterogeneity is not as important as usage heterogeneity. The top 10% of the population in the "*variable behavior*, *average location"* scenario captures 86%, 81%, and 70% of "total" carbon savings from televisions, washers, and dryers respectively, relative to the "*variable behavior, variable geography"* scenario. In contrast, "*variable locations, average behavior"* scenario capture only 29%, 50%, and 32% of "total" carbon savings. It is also interesting to note that even though clothes washers and dryers have the same

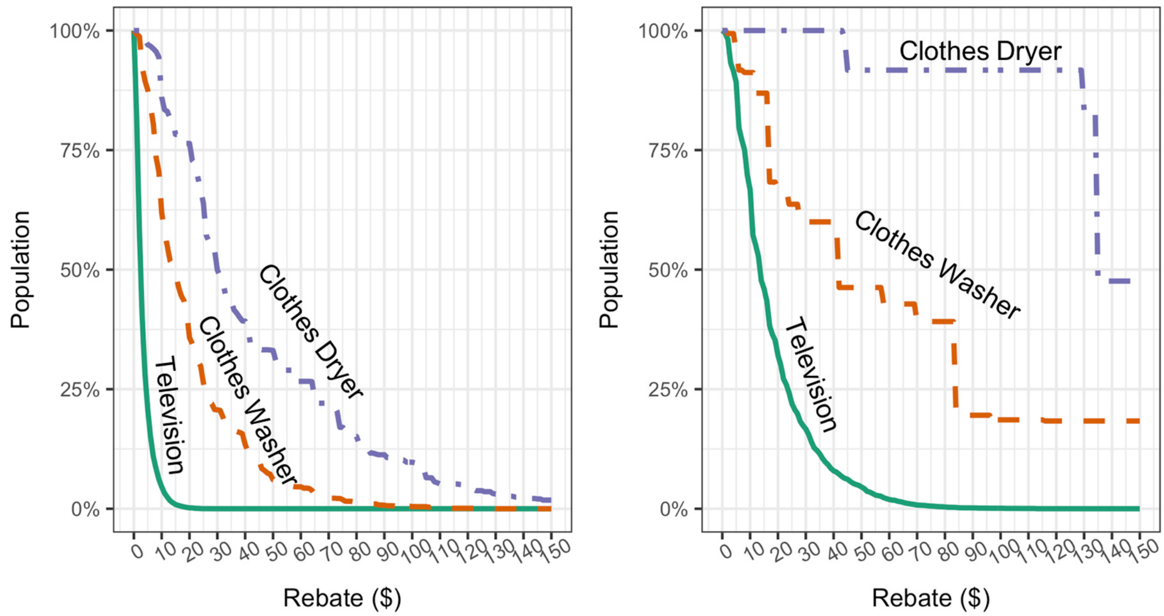

Fig. 5. Left: Percentage of population with Utility Carbon Abatement Cost less than \$48/tonne. Right: Percentage of population with Utility Electricity Abatement Cost less than 12.65 cents/kWh.

usage patterns, washers show a larger range of carbon savings compared to dryers. This is the case because the calculations for washers include stock heterogeneity by technology type and fuel used for heating water. Top-loading washers save significantly greater energy than front-loading washers.

3.4.1. Demographics

The objective of evaluating sub-population demographics is to identify characteristics of those households with higher or lower 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 with at least double the average energy savings. Based on the above discussion of the importance of heterogeneity, behavior is expected to be the main factor differentiating subpopulations. Thus, subpopulations with high savings for washer and dryer are the same because the same behavior applies to both.

All households with a wash load frequency of 1 or less per week have negative NPV for both washer and dryer efficiency upgrades. Most of these household members live alone or live with their partner with no children. Light users of washers, who do 1 or less loads per week, tend to have lower income and are older than general population. 45% of light users earn less than \$30,000, compared with 33% of the general population. These low income light users are often single and elderly with median age of 67 and 87% living alone. Light users with income more than \$30,000 have median age of 57 and 54% live alone. A subpopulation with negative NPV for television is non-existent since the upgrade cost for an efficient television was taken as \$0.

In the case of televisions, households with more than double the energy savings compared to the average consumer watch more than

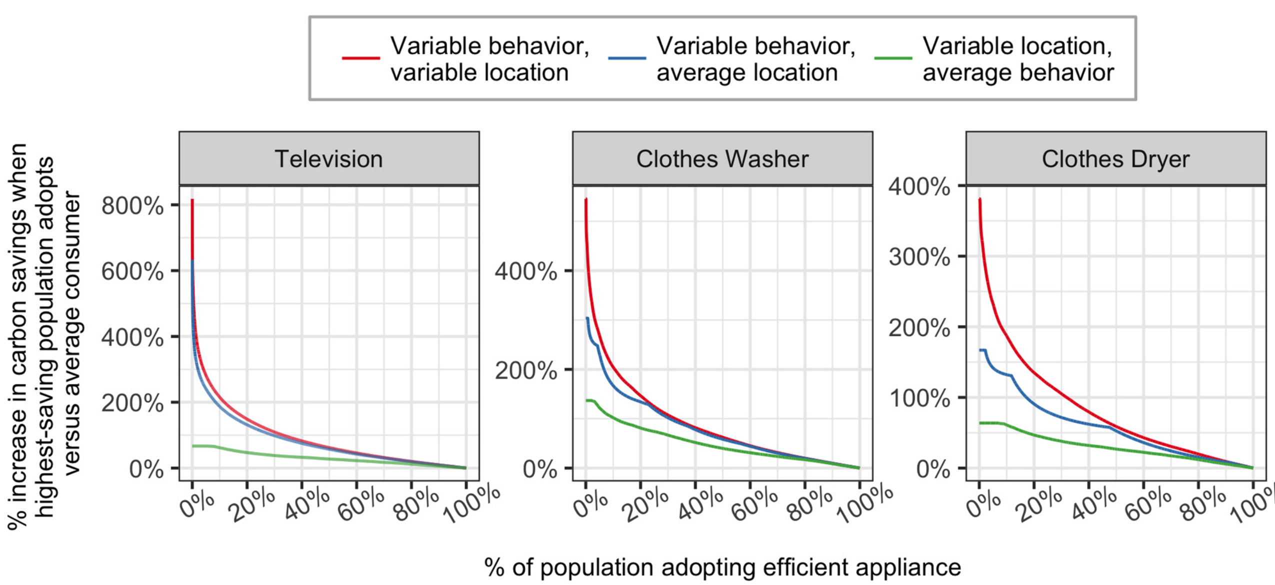

Fig. 6. Increase in carbon savings with an intervention that targets sub-population with maximum savings versus adoption by an average consumer. Effects of behavior and geographic heterogeneity are accounted for separately and also combined. Behavioral heterogeneity (usage pattern) has a larger effect than geographic heterogeneity for all three products. Note that washers also include stock heterogeneity (top versus front-loading), therefore variation is larger than for dryers.

6.6 h/day. The demographics of this segment consists of people who are older, less educated, and typically unemployed. For washers and dryers, the households with load frequency of 10 or more per week save double the energy of average homes. These heavy users of washers and dryer have on average more than 4 members in the household with at least 2 children. 45% of the households in this group earn more than $75,000 per year and 100% of the households have at least one employed member. To summarize, elderly populations tend to use washers and dryers less but televisions more, while families with children use washers and dryvers more. Applying these results to efficiency programs, for example subpopulations who are a good target for efficient televisions are poor targets for efficient washers and dryers.

3.5. Limitations

While the Residential Energy Consumption Survey is a standard and widely used data source for efficiency analysis, it has limitations in describing behavior. Behavior is reported in ordinal bins, e.g. 5-9 loads per week. We derived average values for bins using two assumptions: 1) assigning the numeric value based on mean value of a bin and 2) for extreme bins (frequency of wash loads "1 or less" and "15 or more"), frequencies were assumed to be 1 and 15 respectively. This choice preserves variability but squeezes both sides of the distribution towards the center. Therefore, energy savings and subsequently the NPV of households with usage "1 or less" loads per week are overestimated, while energy savings and NPV of households with usage "15 or more" loads per week is underestimated, i.e., energy savings and NPV could be even larger.

We do not consider technology switching within the observed timeframe. For example, households with top-loading type clothes washer are 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 that of front-loading clothes washers. Front-loading clothes washers typically consume less energy (one-third) and water (one-fourth) as compared to top-loading clothes washers. Therefore, moving from top to front will have larger savings, while the reverse has the opposite effect. Similar scenarios exist in the case of carbon savings when switching from electricity to gas for water heating in a clothes washer and supplying hot air in a dryer.

Other parameters used in the model such as the life span of an appliance, discount rate, difference between ENERGY STAR and baseline energy savings rate are important in determining an accurate savings estimate. The portfolio of models offered on the market changes year by year and even presuming ENERGY STAR estimates from 2016 are exact, the difference between typical certified and non-certified appliances will change over time. These caveats granted, the central point of this manuscript, that behavioral heterogeneity is critical in assessing economic and environmental benefits of appliances, is insensitive to these limitations.

4. Conclusions and policy implications

We found that household differences in behavior (device usage) and geographic variability (electricity prices and carbon intensity of electricity) lead to large variations in the monetary benefits and carbon abatement costs of efficient appliances. Further, the effect of behavioral heterogeneity was found to be larger than geographic variability. Based on the results it can be concluded that heterogeneity should be considered when designing and evaluating energy efficiency programs. Note that there are additional benefits of efficiency programs not assessed in this work. Utility benefits include avoided electricity generation costs (energy and capacity) and avoided transmission and distribution costs. There are also public health and environmental benefits to society due to the reduction of pollutants emitted in the generation of electricity.

Heterogeneity has implications for implementation and evaluation of rebate and other efficiency programs. First, on the implementation side, heterogeneity in consumer behavior implies that targeting high use consumers could be more cost-effective than the usual blanket marketing approach. For rebate programs, this opens the possibility of achieving savings with lower rebates since targeted adopters save more than average consumers. Addressing heterogeneity could also support newer pay-for-performance efficiency programs. These involve utilities compensating consumers monetarily for energy savings (Szinai and Borgeson, 2017). More personalized information for consumers could better inform how much they would save from different interventions, motivating their participation in a pay-for-performance program.

Second, on the evaluation part, the cost-effectiveness of appliance rebate programs is evaluated based on average savings calculations. When behavioral heterogeneity is large, evaluation metrics could be skewed as program participants differ from the average. To address this, utilities can ask program participants to report product usage behavior when filling out the rebate application form.

While we have clarified the economic benefits of more resolved behavioral information, we have not addressed the cost of collection and dissemination of this information. Collection costs increase with accuracy. The least expensive option is to model heterogeneity based on known (or easily obtained) demographic information on households e.g., publicly available data such as census and tax accessor data. Another option is to purchase private data from consumer analytics firms that collect household level demographic data. This data costs around ~2 cents per person but it depends on the quantity of records purchased (Jeremy Groen, Personal communication). While a reasonable degree of heterogeneity presumably correlates with factors such as household size, there is also variability not explained by demographics. A more accurate, though costlier option, is to collect individualized household behavior via questionnaire and/or smart meter data. The cost of obtaining household level behavioral information has been falling with the dissemination of smart meters and development software that imputes the structure of electricity use from meter data. The costs of targeted dissemination of information depends on how it is implemented (Sekar et al., 2016). It is important to note that savings are possible if targeted communication is done in place of current blanket forms, e.g. mailing an efficiency brochure with every monthly bill. We leave the analysis of the benefits and costs of different collection and dissemination schemes for future work.

Accounting for heterogeneity can also inform the design of energy efficiency programs, e.g. what appliances get how much rebate. If a hypothetical rebate portfolio included only the three products studied here, the utility would benefit by focusing on energy-efficient dryer adoption as opposed to televisions and washers. There is also a question of offering differentiated rebates, making them higher for consumer segments that use more. Such differentiated programs may run into conflict with regulatory requirements to serve the public interest - consider the public debate over a rebate program that offered greater rebates to high-income houses (Frank and Nowak, 2016). Depending on the appliance, differentiated rebates could align with social norms, e.g. offering savings to the elderly or households with more children is a common practice.

Units

1 Gallon = 3.78541 l
1 Pound = 0.453592 kg
1 Therm = 100,000 British thermal units
1 t = 1000 kg

Acknowledgements

This research was supported in part by the United States National Science Foundation, Environmental Sustainability Program (grant CBET #1605319). We would like to acknowledge the reviewers of this manuscript, who made very helpful comments and also thank Kathleen Vokes from the United States Environmental Protection Agency for help with ENERGY STAR data.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.enpol.2018.10.035.

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