Residential energy efficiency investment and demand response under different electricity pricing schemes: a hybrid physical-microeconomic approach

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Abstract

This paper expands on a previously-presented methodology that merges the physical nature of energy with microeconomic principles. The physical side informs the amount of electricity used to satisfy services that people desire, while the microeconomic side imposes a utility function for the households to represent its satisfaction. The expansion adds energy efficiency investment to price-based behavioral demand response, and makes our results representative of the long-run steady-state. Several electricity pricing schemes and energy efficiency options are examined, with costs and benefits of each option explicitly modeled in the physical representation.

Performing a modeling analysis for archetypical villas across Saudi Arabia, two key insights are derived:

- The possibility for energy efficiency investment lowers the need for conservation at optimal consumer welfare. Raising monetary incentives that result in less personal expenditure on energy efficiency, households lessen the extent to which they practice conservation.
- As energy efficiency subsidies and electricity prices rise, the difference in household spending on other goods and services widens between the highest efficiency case and no added efficiency. This indirect rebound effect causes a situation where firms may increase their production to meet the additional demand from households for their goods, which will require more energy.

Keywords: building energy model; microeconomics; energy efficiency; electricity pricing; Saudi Arabia

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1. Introduction

Higher energy prices may induce a combination of behavioral changes and investment in higher energy efficiency (Baatz, 2017). When it comes to electricity, Yang et al (2018) detail examples of various strategies for price-based demand response. They include time-of-use (TOU) pricing, which can shift loads between certain times of the day, real-time pricing (RTP), and critical peak pricing. Incorporating energy efficiency, Goldman et al (2010) discuss how efficiency and behavioral price-based demand response can overlap. Although updating building codes would help in alleviating behavioral response, they mention two other types of coordination: combined awareness campaigns and market-driven services. Market-driven services are offered by energy service companies, or ESCOs, which serve customers who are seeking lower energy costs.

Behavioral change alone can be exercised relatively quickly, so its effect dominates a demand response in the short-run. Purchases of higher efficiency, however, require time to materialize due to many reasons, including lack of capital or the seeing the existing units through their economic lives. Plus, energy efficiency purchases differ in their monetary cost, their inconvenience level at the point of installation, and their benefit. For example, a light bulb is less costly to replace and requires less effort to install than retrofitting a dwelling with higher thermal insulation. Taking into account energy efficiency investment along with an energy price change would therefore be indicative of a long-run demand response.

Past studies have argued for a hybrid physical and microeconomic framework to estimate short-run electricity price response (Matar 2018, 2019). The case was especially made for regions in the world that have had low or fixed electricity prices for a prolonged period of time. In this case, econometric estimates would not be indicative of the response new pricing policies warrant. Those previous analyses explored how a household would alter its expenditure among different goods and services in response to a change in the electricity price scheme. The household could not make purchases in efficiency.

Krarti et al (2017) merged a building energy model with a cost-minimization component to assess energy efficiency investment options for households in Saudi Arabia. While the dual problem of a utility-maximization problem is formulated as minimizing cost, the dual problem must contain the utility in the constraints (i.e., what is the minimum cost to achieve a certain level of satisfaction?). This utility constraint is not found in typical cost-minimization problems, and in fact, not contained in the algorithm Krarti et al (2017) apply. For instance, the least-cost approach without consideration for consumer satisfaction would show a demand response that exhibits unrealistically high indoor thermostat settings.

The behavioral component made available through the incorporation of individuals' utility functions is preferred because it better captures their decision-making criteria (e.g., Foxall and James, 2001; Foxall and Schrezenmaier, 2003; Allcott, 2009). Indeed, Allcott (2009) has experimentally shown that applying alternative electricity pricing causes the consumer to first seek conservation avenues. The purpose of this paper is twofold:

- The first is to present energy efficiency purchases, in conjunction with the behavioral price response, in the hybrid mathematical construct used by Matar (2018, 2019).
- Secondly, use that framework to analyze the effects of electricity price changes on household decisions. Households are a heterogeneous population; however, we hope to extract some general insights.

This paper is structured as follows: The next section reviews the recent literature on energy efficiency, the rebound effect, and their relationship with energy prices. We lay out the approach taken in this analysis in the subsequent section, following by the electricity prices we consider. We conclude by presenting and discussing the results.

2. Energy efficiency policy, energy prices, and the rebound effect

Gillingham et al (2009) provide a succinct review and discussion of energy efficiency policy. They identify potential market failures that may cause over- or under-investment in energy efficiency. Major reasons for failure include improper accounting of environmental externalities, energy pricing that deviates from its marginal cost of supply, and capital constraints that consumers may face. For instance, setting energy prices below their marginal costs of production does not send the consumer the appropriate price signal to invest in efficiency. Energy companies would observe lower demand-side investment than is optimal based on their production costs, and thus require to operate or invest in more capacity.

Under-investment in efficiency may call on the power utilities to provide financial incentive packages to consumers, like investment credits, tax deductions, or loans. The cost effectiveness of past incentive programs targeted at energy efficiency adoption has been debatable. Friedrich et al (2009) find that energy efficiency programs in the US resulted in a cost savings of 1.6 to 3.3 cents per kWh. These savings show that energy efficiency is cost-effective compared to the marginal cost of supplying electricity for the power generators. This is almost universally the case, with the exception of generators that receive fuel at low administered prices; some countries in the Gulf Cooperation Council (GCC) offer low fuel prices to power utilities and industry (Wogan et al, 2017). In this scenario, energy efficiency purchases would be limited in their cost-effectiveness. Gillingham et al (2009) review a few more studies that show past programs may have slightly raised the likelihood for investment. Although the programs exhibited a significant number of participants, many of whom were identified as would-be adopters even without the incentives, or “free-riders”. Alberini and Bigano (2015) take into consideration potential free-riders in a survey, and provide evidence that households in Italy who were not going to invest in energy efficiency would be more likely do so under rebates.

Lack of information about the costs and benefits of higher energy efficiency may also be a hindrance. Ramos et al (2015) reviewed the effectiveness of energy certificates and labels, energy audits, and feedback to the consumer. Energy certificates pertain to information accompanying the appliances that would assist the customer in making purchase decisions. The authors found that feedback and labels were most effective of the three options at diminishing this failure; however, they found that the impact of energy audits were mixed. Although, in-home displays showing energy use before and after the implementation of efficiency provide similar information as an energy audit or feedback.

There is also a wide body of literature that suggests there could be direct rebound effect as a result of energy efficiency improvement (e.g., Gillingham et al, 2016; Wei and Liu, 2017). The direct rebound effect refers to the behavioral phenomenon where the actual energy savings as a result of higher energy efficiency are lower than would be expected from engineering computations. Gillingham et al (2013) discuss that the literature has predominantly analyzed this issue using a costless energy efficiency, and that its effect, even if it arises, should not be a hindrance to energy efficiency programs. Although the direct rebound effect is limited, Alfawzan and Gasim (2019) empirically find that it reduces social welfare. This ties into our study because any potential incentive program could result in a near costless efficiency improvement for the household.

Since some households may have more room in their budgets after higher energy efficiency is introduced, especially if they receive financial support, they may spend more on other goods. If they do, that warrants additional energy consumption for those goods' production. This is called the indirect rebound effect (e.g., Barker et al, 2009; Gillingham et al, 2013; Thomas and Azevedo, 2013). de Miguel et al (2015) report that little attention has been paid to estimating it, and that analyses that have generally addressed it in the context of lower energy prices, as opposed to rising disposable income. We will investigate if the results indicate the presence of indirect rebound, resulting for higher disposable income, by examining the households' expenditures.

Moreover, households could be paying real-time prices for the electricity use, which would be lowered if their power demand reduces as a result of conservation and/or efficiency. This is because as demand lowers, the equilibrium point may shift down the supply curve as the operation of more expensive marginal power generators lessens. So in this case, there is a two-sided benefit to energy efficiency for the household:

- It reduces the amount of electricity (and associated expenditure) used, but also,
- lowers the average electricity price paid.

This is not a universal statement, however, as many countries offer a fixed electricity pricing structure for households. Although the marginal electricity supply cost would reduce due to lower demand, the price paid by households would remain unchanged; at least for some time, if the region revises electricity prices periodically.

China is a country where electricity pricing is administered (Yang et al, 2018). In the Chinese context, Lin and Liu (2013) show that if energy efficiency measures in the household are coupled with higher electricity prices and the associated investment costs, the direct rebound effect could be negligible, if not negative (as the price keeps rising). Because energy efficiency is typically adopted by an environmentally-conscious household or due to higher energy prices, we expect a minimal direct rebound, particularly if the household bears the investment. The GCC countries also administer fixed electricity prices, which is exemplified by the prices in Saudi Arabia in a subsequent section.

3. Technology adoption by households

Previous research reveals that the adoption of new technology by households is not instantaneous. It takes years for a heterogeneous population, such as that of households, to replace existing stock of appliances or equipment; especially if the technology is new and future cost (and price) reductions are expected. As Jaffe et al (2004) mention, technology adoption is characterized by an S-shaped curve (called "the diffusion curve" from here on out). Adoption is typically slow in the beginning and end of this curve, exhibiting a large uptake in the in-between years. Of course, we can hypothesize that the shape of this curve differs from one energy efficiency measure to another. This depends on the up-front prices of these options, their expected service lives, the capital constraints each household faces, and the energy-saving benefits conveyed to households as a result of the technologies' adoption.

Agent-based models (ABM) have been used in modeling the diffusion of technologies over time. Cao et al (2017) illustrate the diffusion of various lighting technologies using an ABM for a hypothetical residential community. They produce curves for various scenarios over 25 years. None of their curves came close to 100 percent adoption of light-emitting diodes (LED), although the banishment of incandescent lights resulted in the highest adoption. Their diffusion curves were mostly characterized by lower positive slopes than one would expect from an S-curve. Also using an ABM, Friege (2016) analyzes the adoption of higher thermal insulation for a city in Germany. Although they do not show a diffusion curve per se, they report the average adoption rates as an average over a ten-year period. Although none of the studies reviewed assessed the effects of price-induced energy efficiency investment.

4. Methodology and data input

4.1 *Residential electricity use model*

Matar (2018, 2019) proposes a linkage between a physical building energy model and a household whose decisions are consistent with microeconomic fundamentals. Previous analyses explored demand response measures as a result of different electricity pricing schemes. They examined the demand response measures that are exercised in order to maximize a household's utility.

We extend that model to include the purchase of energy efficiency measures. In addition to applying different electricity pricing schemes and behavioral demand response, like adjusting the thermostat in the summer or the spring and fall, we assess how those different prices influence energy efficiency adoption. The model is also expanded to represent archetypes of a villa in multiple regions in Saudi Arabia. The regional breakdown takes the Saudi Electricity Company's (SEC) operating areas; southern, western, central, and eastern. The regional dimension considers the climatic differences across the country, and therefore the differing energy efficiency needs.

Appendix A contains the data calibration of the physical component. We calibrate the model for regional archetypes of villas, apartments, and traditional houses to match the actual electricity use data in 2017; however, we only conducted the analysis for the villas in all four regions. This way, the villas used in the paper have some empirical consistency with 2017 data. Plus, the model will be calibrated for future research purposes. Particularly linking the demand-side model with a multi-sector energy system model, like the KAPSARC Energy Model (KEM).

Figure 1 illustrates the coupling of the two components. In this linkage, we suppose the households have set utility functions with given preferences. This essentially makes the utility functions' preferences normative, or how the utility functions of the set of households "should" be shaped. Although we are ultimately identifying the point at which the utility is maximum, we are not strictly maximizing it in the optimization problem sense. We are only computing its value for all possible combinations of price response measures and energy efficiency adoption, assuming a budget constraint and that household(s) would have the same utility functional form.

Past analyses with the framework used a Cobb-Douglas functional form. Although we do not necessarily optimize directly, we have opted to apply a more flexible function in this study. A constant elasticity of substitution (CES) utility function is used, as shown by Equation 1. While the substitution elasticity is fixed, the own-price elasticity of the goods' demand is allowed to vary based on the expenditure shares. x_i are the electricity uses by service, in MWh, and ϕ_i are adjustment factors that estimate the utility gained by the installation of energy efficiency. In other words, ϕ_i adjust any decreased use of electricity due to energy efficiency by raising $x_i\phi_i$. The consumption of other goods and services, in monetary terms (all of the individual elements in the set *i*); the price of other goods and services is set to unity. Electricity use quantities related to air-conditioning and lights, and the remaining electricity use, are defined by Equations 2-4.

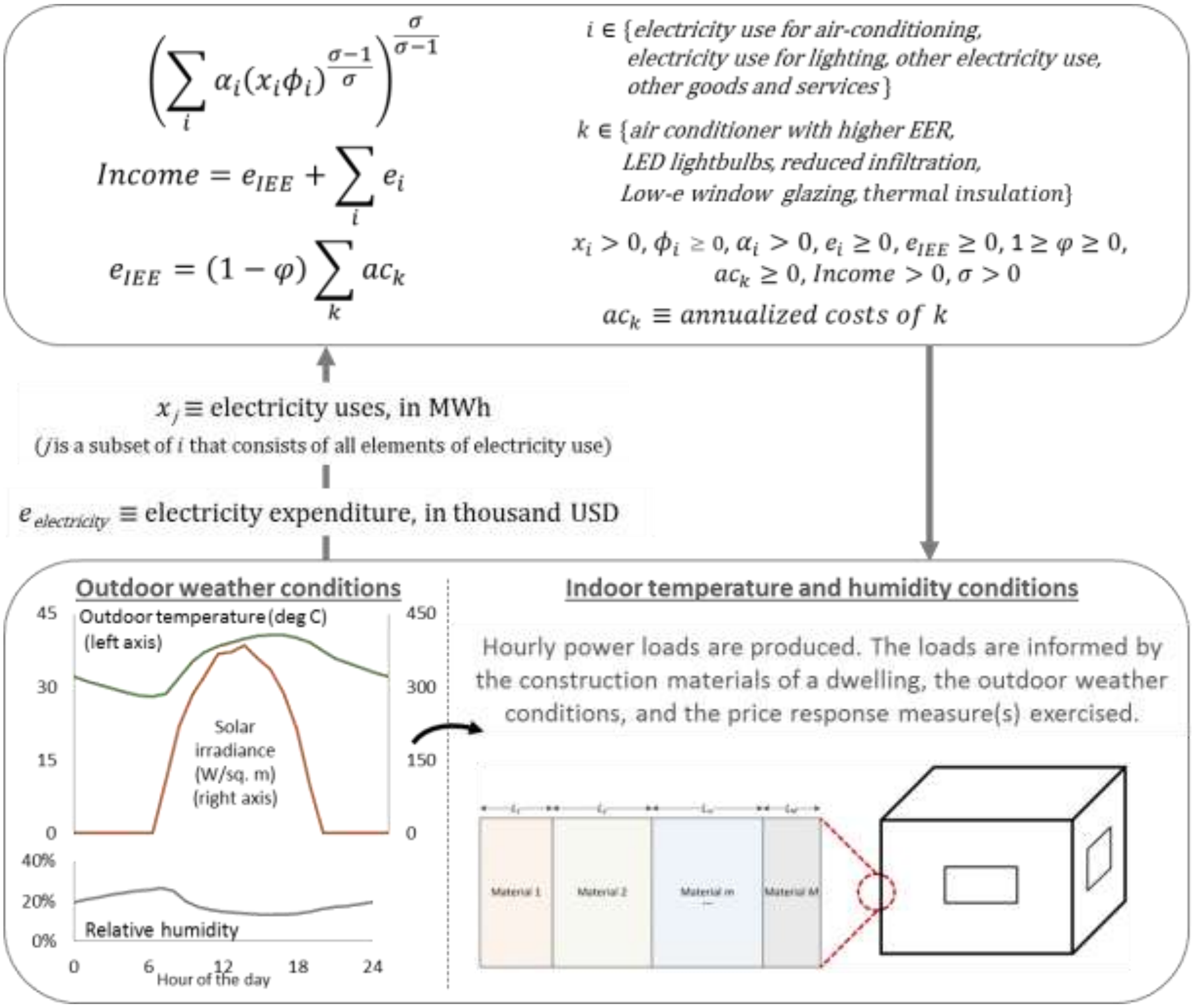

Figure 1 – Coupling of the physical and utility-maximization components

$$Utility = \left(\sum_i \alpha_i \left(x_i \phi_i\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{1}$$

$$x_{AC} = \sum_{season,hour,daytype} P_{AC_{season,hour,daytype}}\, Dayinseason_{season,daytype} \Delta t \tag{2}$$

$$x_{lighting} = \sum_{season,hour,daytype} P_{lighting_{season,hour,daytype}}\, Dayinseason_{season,daytype} \Delta t \tag{3}$$

$$x_{other\ electricity} = \left[E_{electricity} - \left(x_{AC} + x_{lighting}\right)\right] \tag{4}$$

${P_{AC}}_{season,hours,daytype}$ are the hourly loads for the heating, ventilation, and air-conditioning (HVAC) system by season and day type. We consider two types of day: weekends/holidays and weekdays. Similarly, ${P_{lighting}}_{season,hours,daytype}$ are the hourly loads stemming from the use of lighting. $Dayinseason_{season,daytype}$ are the number of days in each season by type. Δt is the hourly resolution during the day, which in our model is taken as unity.

ϕ_i for electricity use are only different from unity when energy efficiency measures are tested, and their values are not affected by behavioral response. ϕ_i for air-conditioning and lighting electricity use are defined by Equations 5 and 6, respectively. The values of ϕ_i are always one for other terms in the utility function. Services, such as lighting use, affect the cooling load in the dwelling (non-linearly), thus all heat gains are considered for the air-conditioning adjustment. EER is the energy efficiency ratio of the air-conditioning unit, IHG is the sum of total internal heat gains from appliances and lighting during the year, SHG is the sum of direct and diffuse solar heat gain through windows during the year, ΔT is the summed differences in temperature between the internal surfaces of the walls and roof and the desired initial indoor temperature setting, and ω is the heat gained due to infiltration. Heat gains are defined in units of power.

ΔT is incorporated to capture the effect of more stringent thermal insulation. s is the share of each type of heat gain in total cooling load at the initial, or calibrated, state for each region; it stipulates that improvements in energy efficiency are not given the same weight. EER is a characteristic of air-conditioners that relates electricity use to cooling load, and thus is not part of it. Each set of values for any scenario is related to the initial state, $(\cdot)_{initial}$.

In Equation 6, the power needed to meet the initial illumination requirement at the calibrated state ($N_{initial}$) is divided by the power needed for each scenario to meet that same initial requirement (N).

$$\phi_{AC} = \frac{EER}{EER_{initial}} \left(\frac{IHG_{initial}}{IHG}\right)^{S_{IHG}} \left(\frac{SHG_{initial}}{SHG}\right)^{S_{SHG}} \left(\frac{\Delta T_{initial}}{\Delta T}\right)^{S_{wr}} \left(\frac{\omega_{initial}}{\omega}\right)^{S_{inf}} \tag{5}$$

$$\phi_{lighting} = \frac{N_{initial}}{N} \tag{6}$$

α_i are the preferences, and they sum to unity for all *i*. The households were calibrated to have preference shares for electricity that range between 5 and 7 percent, depending on region. This calibration was performed by starting at a near-zero electricity preference setting, and slowly raising that preference until the households no longer responded behaviorally to the 2017 electricity tariffs. We further disaggregate the preference share devoted to electricity to its various components. We use estimates based on the 2011 consumption shares reported by Faruqui et al (2011) for a household in Saudi Arabia; these metrics are shown in Table 1. The preference share of other goods and services is just 100 percent minus the electricity preference share. Finally, σ is the elasticity of substitution, and the calibrated value is 0.9.

Electricity end-use	Shares of electricity consumption (percent)
Cooling	70
Lighting	5
Other	25

Table 1 – Estimated electricity use breakdowns for a household in Saudi Arabia (source: estimated by the authors from Faruqui et al, 2011)

To calculate $x_{other\ electricity}$, the total contribution of electricity use by air-conditioning and lighting are subtracted from the total electricity use ($E_{electricity}$). Its value changes based on electricity pricing and efficiency scenarios.

The budget constraint is shown by Equation 7. $Income$ is the households' average annual income by region. For the time being, it is calibrated based on the average 2013 income of a household in each region, as shown in Table 2 (Central Department of Statistics and Information (CDSI), 2013). e_i are the expenditures on electricity and other goods and services. Expenditure on electricity may be computed based hourly prices or the present progressive pricing structure that is found in Saudi Arabia. e_{IEE} is the annualized investment and maintenance cost required for a particular energy efficiency measure. We have only included the expenditure on higher energy efficiency in the income constraint, as its effects in the form of lower electricity use appear in the utility function.

$$Income = e_{IEE} + \sum_i e_i \quad (7)$$

Region of Saudi Arabia	Annual household income (thousand USD)
Southern	34.81
Western	31.71
Central	33.49
Eastern	40.59

Table 2 – Annual household income by region of Saudi Arabia (source: CDSI, 2013)

Power utilities or the government – since some power companies are state-owned – may want to establish energy efficiency programs that provide incentives to households. This may arise if the utilities find additional avoided costs that are higher than the cost of the incentives. Incentives may also be warranted if there is under-investment in efficiency due to electricity prices being lower than their marginal cost of generation and transmission, or if the households have liquidity constraints (Gillingham et al, 2009). This potential deviation in customers' load profile to that that would result in optimal avoided costs is referred to as the energy efficiency gap.

Thus, we include Equation 8 that would reduce the purchase cost of the energy efficiency measures for the household. This equation ensures that any monetary transfer to households is specifically used on energy efficiency options.

$$e_{IEE} = (1 - \varphi) \sum_k ac_k \quad (8)$$

ac_k are the annualized costs of the energy efficiency options, k, defined in the next sub-section. φ is a parameter that denotes the portion of the cost that is taken up by the power utilities or the government, and it ranges from zero to unity; its value is fixed to zero for the calibrated case. We will observe how the model solution differs for several values of φ. To circumvent the issue of free-riders, who would invest in energy efficiency anyway, money equivalent could only be distributed to the households whose annual income is below the mean in each region. Operationally, this means a single physical archetype may be split to have two versions of that apply to households by income. The incentives only apply to households whose income is below the average. Due to lack of data, and the fact that we only do this analysis for villas, we only mention its possibility. We will incorporate a non-zero φ for all households alike.

This analysis also incorporates the appliance shifting algorithm used by Matar (2017). We will summarize the appliance usage approach here, although more detail is provided in that paper. Only appliances used for discretionary purposes, such as consumer electronics, washing machines, and clothes dryers are considered eligible for load shifting. Although appliance loads may be shifted, this program assumes the overall usage of appliances – summed over hours – remains fixed. It feeds the physical model with an appliance use schedule, and ultimately informs the utility-maximization problem.

Following Setlhaolo et al. (2014), we here take an approach where households may react by considering both the cost of electricity and a non-monetary cost of inconvenience when shifting appliances; this sum of the two cost components is termed the *total perceived cost*. We assume that households are provided with electricity prices sufficiently in advance, and thus have the time to react accordingly and minimize their total perceived cost concerning appliance use. The cost of inconvenience increases more rapidly the further in time an appliance is shifted.

$$\min \ \left\{\sum_{(h,s,d,r)}\left[\pi_{h,s,d,r}L_{h,s,d,r}\Delta t_h\right] + \sum_{(a,h,h2,s,d)}\left[\gamma_{inconv}NU_{a,h,h2,s,d}\left(t_h^{new} - t_{a,h2,s,d}^{original}\right)^2\right]\right\} \tag{9}$$

In Equation 9, $\pi_{h,s,d,r}$ is the hourly price of electricity throughout the day (*h*), and may vary by season (*s*), type of day by weekdays and weekends (*d*) and regions (*r*). $L_{h,s,d,r}$is the total direct power load resulting from the use of discretionary appliances. $NU_{a,h,h2,s,d}$ is a binary variable that equals unity if the device, *a*, is turned on and zero when it is off. It keeps track of when the device was originally used (*h2*) and to what point in time its use is shifted (*h*). Δt_h is the discrete time step and is equal to one hour in our analysis. γ_{inconv} denotes the rate of increasing cost to the household by shifting their use of an appliance further away from its original time of use; this is estimated by the authors as 10 USD per square hour. $\left(t_h^{new} - t_{a,h2,s,d}^{original}\right)^2$ represents the extent of deviation of appliance use, and yields a value that increases in quadratic fashion the further in time households shift their use. Thus, the household must consider the trade-off between the cost of electricity and a perceived cost of inconvenience when electricity prices are raised.

All in all, the residential demand assessment examines different combinations of price-based demand response, including appliance load shifting, and energy efficiency measures. The model outputs the household's utility value and hourly load curves for each case, but because the results can be cumbersome, it identifies the case that maximizes the utility. The different combinations of cases are detailed in Table 2.

4.2 *Energy efficiency adoption*

As shown in Table 3, we consider an agent who has a finite set of possible energy efficiency choices. This approach is, in a sense, more realistic. It breaks down the investment options into discrete elements, rather than a continuous domain of infinitely possible choices. We examine a subjectively-defined set of efficiency choices in this analysis. Other analysts may desire to look at alternative definitions. The options are upgrading the air conditioner from an average energy efficiency ratio (EER) from the calibration value to 15 BTU/(Wh), sealing any cracks between doors or windows and walls in the thermal envelope, investing in low-e window glazing, retrofitting more stringent thermal insulation, or replacing all lightbulbs with LED lightbulbs; the calibrated EER value is 7 BTU/(Wh), as detailed in Appendix A. The household can also merge the higher EER, reduced infiltration, and LED lights all together.

<table>
<tr><th rowspan="3">Energy efficiency cases</th><th colspan="4">Demand response measures</th></tr>
<tr><th colspan="2">Thermostat set-point adjustments</th><th colspan="2"></th></tr>
<tr><th>Summer, spring, and fall</th><th>Additional adjustment during the peak in the summer</th><th>Turning off lights</th><th>Appliance load shifting</th></tr>
<tr><td>Without higher energy efficiency</td><td rowspan="7">Incrementally raising the set-point from 0 ^{o}C to 3 ^{o}C in the summer, or from 0 ^{o}C to 1.5 ^{o}C in the spring and fall.</td><td rowspan="7">The household has the option to raise the thermostat set-point further from the summer setting by 0.5 ^{o}C.</td><td rowspan="7">Incrementally lower the lighting requirement in the dwelling.</td><td rowspan="7">The household may shift its appliances use based on its perceived cost, which is the sum of the monetary cost and a cost of inconvenience.</td></tr>
<tr><td>Air-conditioning with average EER of 15 BTU/(Wh)</td></tr>
<tr><td>Reduced infiltration to 0.30 ACH</td></tr>
<tr><td>Low-e windows</td></tr>
<tr><td>More stringent thermal insulation (apartments and villas only)</td></tr>
<tr><td>100% LED adoption</td></tr>
<tr><td>The combination of higher EER, sealing cracks, and LED adoption</td></tr>
</table>

Table 3 – Combination of price-base demand response and energy efficiency measures analyzed

In the calibrated case, we estimate that all households have an infiltration rate of 0.65 to 0.80 air changes per hour (ACH), depending on region. We further stipulate that lighting technologies currently adopted are incandescent bulbs, linear fluorescent lighting, and compact fluorescent bulbs, as reported by the General Authority for Statistics (GAstat) (2017a). Windows in the calibrated dwellings are assumed to be single-glazed.

The materials of the walls and roof are listed in Table 4 for each residential archetype. GAstat (2017b) mentions that all villas and apartments are built using concrete, whereas 65 percent of traditional houses are built using adobe, or mudbricks. The remaining 35 percent of traditional houses is made of concrete, but we just took the majority to represent a single archetype and manage the model size. The thermal diffusivity and conductivity of each material, as well as the solar emissivity and absorptivity of the external material, are derived from McQuiston et al (2005). The thermal insulation properties in the more stringent insulated cases are also shown.

	Materials of walls and roof, from exterior surface (top) to interior surface (bottom) [thickness, depending on region]
Calibration for apartments and villas	Cement plaster [2.0 cm] Concrete [15.0 cm (20.0 cm in the western area)] Cement plaster [2.0 cm]
Calibration for traditional houses	Mud brick [19.0 cm] Mortar [2.0 cm] Mud brick [19.0 cm]
More stringent thermal insulation for villas, as used in the analysis	Cement plaster [2.0 cm] Concrete [13.0 cm] Polystyrene insulation [2.5 cm] Concrete [13.0 cm] Cement plaster [2.0 cm]

Table 4 – Construction materials used in the calibration and the stricter thermal insulation cases (author assumptions)

Each efficiency option has a purchase cost that is annualized over its designed life using a discount rate of 30 percent; this is in line with Harrison et al (2002) and Enzler et al (2014), who report an average discount rate of 28 percent for individuals in Denmark, while estimate an even higher value for Switzerland. This effectively means households who discount at 30 percent are impatient relative to ones that have lower values, and patient relative to ones that have higher values. We estimate that any purchases do not increase the operation and maintenance cost over the base case. The costs used in this analysis are summarized in Table 5. For the scenario where measures are combined, the associated measures' costs are aggregated. For completeness, we will examine the effect of this assumption on the results.

The levels of thermal insulation, reduced infiltration, and/or how much heat is gained through the windows will affect the maximum cooling load [$\max(\dot{Q}_{cooling})$] that a household experiences throughout the year. That will influence the number and cost of air conditioners needed by the household. Therefore, the cost of new air conditioners is formulated as a function of the maximum cooling load in each energy efficiency and demand response case. Since the cooling load is in the units of power, and air-conditioning capacity is marketed in units of energy, dt is the time increment used. We assume the air-conditioning unit cost includes installation.

Energy efficiency measure	Full purchase cost (USD per household)
Air conditioners with average EER of 15 BTU/Wh	$c_{AC} \cdot \max\left(\dot{Q}_{cooling}\right) \cdot dt + L_{AC}$
Sealing cracks around windows, doors, power outlets, and lighting fixtures	$c_{seal} \cdot TFA$
Low-e windows	$c_{window} \cdot TGA + L_{window}$
More stringent thermal insulation	$c_{thinsul} \cdot ESA + L_{thinsul}$
100% LED adoption	$\dfrac{c_{LED} \cdot I \cdot TFA}{\varepsilon \cdot r}$

Table 5 – Full purchase costs of energy efficiency measures, in US dollars (source: author estimates based on Austrotherm Insulation (2017) for thermal insulation, and online retailers for the rest; c_{AC}=6.9 US cents per BTU of capacity; c_{seal}=2.15 USD per m^2; c_{window}=211 USD per m^2; $c_{thinsul}$=10 USD per m^2; c_{LED}=4.4 USD per bulb)

Furthermore, ε stands for LED bulb efficacy in lumens per W, r is power rating of the bulb, TFA is the total indoor floor area of the residence, I is the illumination required, which changes based on conservation case, ESA is the total area of the walls and roof, TGA is total glazing area, $L_{(\cdot)}$ are the labor costs for installing air-conditioners, windows, or thermal insulation, and $c_{(.)}$ are the costs per unit for each efficiency measure. $c_{(.)}$ are in USD per BTU of capacity for air conditioners, USD per lightbulb for LED, and USD per square meter for windows, thermal insulation, and a stronger seal. ESA, TFA, and TGA differ by region and residence type, based on the calibration described in Appendix A. Since we could not find sources to reference, L_{AC}, L_{window}, and $L_{thinsul}$ are estimated to be 500, 1,000, and 10,000 USD, respectively.

For example, the full costs of the more-efficient air conditioner when only its adoption is considered are calculated to be 1,619, 3,028, 3,126, and 3,541 USD per household in the southern, western, central, and eastern regions of Saudi Arabia, respectively, depending on regional climate. The full costs of low-e windows is dependent on dwelling size, and ranges between 3,665 and 4,806 USD for all regions. The selection of any combination of these energy efficiency cases will entail changes to how the model sets the purchase costs. Applying more efficient lighting or sealing the thermal enclosure will influence how much heat is transferred by the light bulbs or the outdoor air into the indoor air, and thus affect the – maximum – cooling load that a household would exhibit.

Although the most economical efficiency options may be chosen by the model, the service life of much of the existing stock of equipment may not have expired. This, along with other factors, like lack of information transfer about the measures to all households, a short duration of stay at a given location, or capital constraints for a portion of the heterogeneous households, may delay the economically optimal adoption of energy efficiency. Moreover, some households may exhibit extra (non-monetary) costs related to the effort needed to go out and buy the materials. Diffusion curves, like those referenced by Jaffe et al (2004), are exhibited in real-life. Hypothetically, each investment option has its own curve.

5. Electricity pricing options and efficiency programs in Saudi Arabia

A slight electricity price rise may only warrant a behavioral change (e.g., managing the thermostat), but a larger increase may bring higher energy efficiency into play. Higher efficiency may even lessen the need to adjust behavior. We can observe any of these situations by analyzing different electricity pricing schemes in conjunction with the households' income. We examine three electricity pricing cases, as summarized in Tables 6 and 7:

- The progressive pricing structure that was applied in Saudi Arabia in 2017. Pricing for residential customers consisted of the progressive prices shown in Table 6. The structure of the prices is 'progressive' because even if the household used more the 2 MWh, it paid 1.33 cents per kWh for the first 2 MWh. This scenario is titled *2017 pricing*.
- The changes made to the progressive pricing structure in 2018. The Electricity & Co-generation Regulatory Authority (ECRA) revised the electricity tariffs on January 1st, 2018, for the consumption brackets below 6 MWh per billing period. This pricing policy is still ongoing as of 2019. Although the government introduced a program to compensate households based on their income (Citizen Account, 2018), we have not distinguished households by income level in this analysis. This scenario is titled *2018 pricing*.
- A time-of-use (TOU) price that stipulates a flat tariff of 5 cents per kWh is charged throughout the year except for the summer during the system peak hours in Saudi Arabia. Then, a 15-cents-per-kWh charge is imposed. This scenario is titled *TOU pricing*.

Monthly use (MWh)	Pricing in 2016 and 2017 (US cents per kWh)	Pricing in 2018 (US cents per kWh)
≤ 2	1.33	4.80
2 < and ≤ 4	2.67	
4 < and ≤ 6	5.33	
6 <	8.00	8.00

Table 6 – Household electricity pricing from 2016 until 2019 (sources: ECRA, 2016, 2018)

The computation of the total electricity cost is detailed by Matar (2018), where the model can aggregate the electricity costs whatever the pricing scheme applied. We could have adopted a real-time pricing scheme had we analyzed apartments and traditional houses, as well, and linked the framework with a supply-side power system model. Then, the marginal cost of electricity generation and transmission is set as the price. Prices in this case would not only vary regionally depending on power generation mixes and inter-regional transmission, but also temporally as electricity demand varies throughout the year. The prices would be determined by iterating between the framework put forward in this paper and a supply-side model to find the equilibrium state (i.e., the point at which electricity demand and electricity marginal generation costs converge). This idea could be part of future work.

Time of year	TOU electricity price scheme (US cents per kWh)
In the summer months during the peak hours (from 12 pm to 5 pm)	15.00
Outside of the summer peak hours, including all other seasons	5.00

Table 7 – TOU electricity price scheme used in our analysis (source: author's assumption)

Furthermore, Saudi government agencies have applied energy efficiency labels, stricter minimum standards for air conditioners and thermal insulation, and financial support for efficiency purchases; many of which were implemented in anticipation of electricity price increases. Efficiency labels were introduced by the Saudi Energy Efficiency Center (SEEC) (2018) for air conditioners, refrigerators, and washing machines in the past several years. The labels are used to inform the customer of the appliances' energy use characteristics. SEEC has also imposed, along with the Saudi Standards, Metrology and Quality Organization (SASO) (2014) a minimum EER of 11.5 BTU/Wh at the lower ambient temperature rating (T1) for new air conditioners. There are also reports, conveyed by the Makkah Newspaper (2018), that beneficiaries of the Citizen Account, a program designed to support lower-income households through energy and non-energy price increases, will receive financial support to buy more-efficient air-conditioning units.

6. Results and discussion

6.1 Electricity use by households in a steady state and energy efficiency incentives

The calibrated state takes a 'short-run' view, and therefore does not consider any added efficiency. Given that our modeling approach considers the impact of investment in energy efficiency using their annualized costs, the results presented offer a glimpse into the steady state; the values obtained for the adjustment factors ϕ_{AC} and $\phi_{lighting}$ are presented in Appendix B. Table 8 shows the model results for aggregate electricity use by households in villas across Saudi Arabia. The table juxtaposes the effects of various electricity pricing schemes and that of energy efficiency subsidy on electricity use. It is worth keeping in mind that the energy efficiency aid is only applicable to energy efficiency purchases. The corner top-left cell shows the base case with the 2017 electricity prices and efficiency investment. Households in villas would use about 46.58 TWh of electricity per year in the long-run, or about a third of total residential use.

		Incentive level (as a percentage of the measure's purchase cost not covered by the household)	
		None	50%
Electricity price scheme	2017 pricing	46.58	29.74
	2018 pricing	29.37	29.74
	TOU pricing	29.07	29.67

Table 8 – Total electricity use in villas in Saudi Arabia for the electricity price and incentive cases (units in TWh)

There is some slight energy efficiency investment in the base case. There are some efficiency cases, like the adoption of LED lighting and sealing cracks around the dwelling, which yield a larger benefit in the long-run than their cost. In the long-run, the annualized costs of these measures pale in comparison to the realized electricity use reduction. LED lights consume less electricity than, for example, incandescent bulbs. This may augment the use of heating in the winter months, but would lower the extent to which cooling is needed in the summer months. Furthermore, Figure 2 shows the hourly load curves in the summer for some of the scenarios. The spikes are reflective of our assumption for the appliance use schedule.

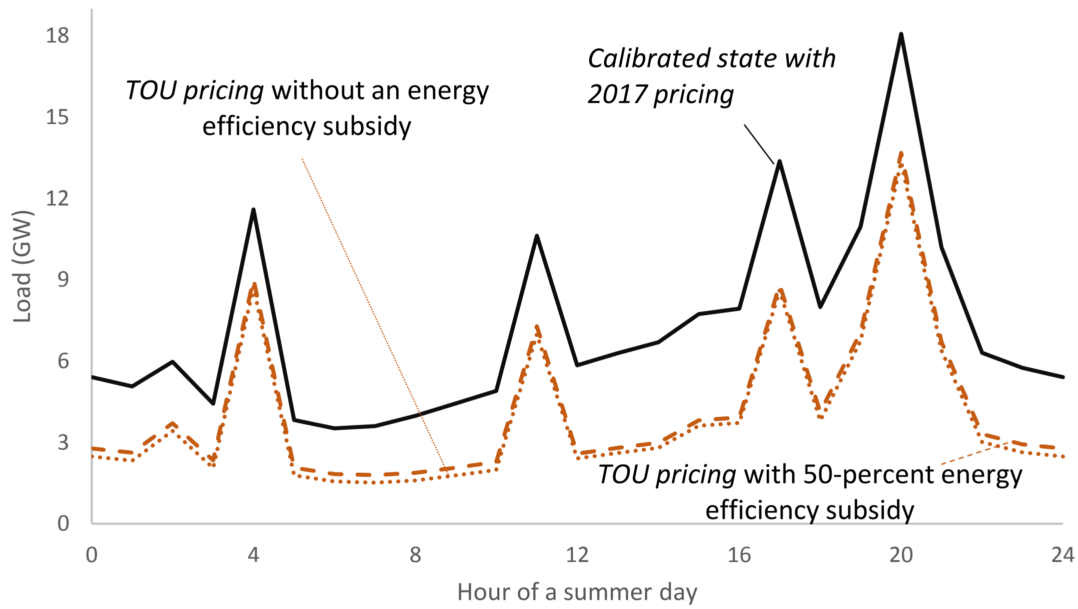

Figure 2 – National aggregate chronological power load curves in the summer corresponding to select electricity price and incentive cases shown in Table 8

Table 8 and Figure 2 highlight the ultimate result, but we can delve deeper into the 'decision' space and extract information about the specific behavioral and efficiency responses that caused these use metrics. The results indicate that, at optimality in the long-run and without incentives, households only behaviorally respond to the 2017 electricity prices by switching off lights. On top of that behavioral response choice, households in all but the southern region also moderately adjust the thermostats in the summer by 1.5 ^{o}C with *2018 pricing*; the climate in the south of Saudi Arabia is less extreme. Under *TOU pricing*, the summer thermostat adjustments are more drastic in all but the southern region. Also, the thermostat in the peak hours during the summer is raised by an additional 0.5 ^{o}C with *TOU pricing* applied.

With 2017 electricity prices and no incentives, all archetypical villa residences maximize their welfare when they only adopt LED bulbs in the long-run. This is rational, as the costs of LED bulbs over their designed life compared to their electricity use reduction are more attractive than the incandescent bulbs of the status quo. This is shown by Figure 3 for the central region, where the LED efficiency scenario maximizes archetypical household's utility at the optimal behavioral state compared to no added energy efficiency. Although higher air conditioner efficiency would produce lower utility on its own, packaging it with LED bulbs and reduced infiltration would yield higher satisfaction relative to doing nothing. With the alternative electricity pricing schemes, the combination of higher EER, reduced infiltration, and LED maximizes the utility relative to the 2017 pricing and no added energy efficiency. Raising electricity prices and practicing conservation alone yields lower consumer welfare than if coupled with efficiency purchases.

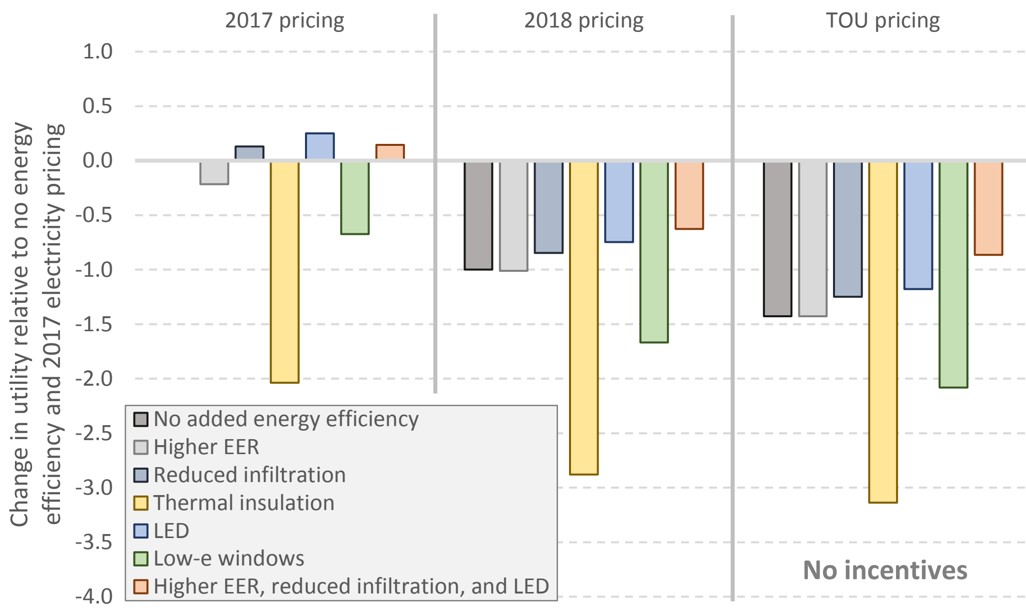

Figure 3 – Effects of the various energy efficiency measures on the welfare of households living in a villa in the central region of Saudi Arabia (no incentives)

The change in utility associated with the packaged energy efficiency measures is not derived from the utility changes of any one measure implemented alone. Efficiency measures' effects on the power load cannot be summed, and as Matar (2016) shows, their compounding electricity reductions are non-linear. In other words, there is a diminishing marginal benefit that is non-linear gained by installing energy efficiency. For example, we see that the effect on the households' welfare by installing more-efficient air conditioners as the only option differs from adding it with other options.

In Figure 4, we see that the consumers' efficiency choice is not affected by 50-percent credits under the alternative electricity prices. The combined measures case still yields the least reduction in welfare in the alternative pricing scenarios. Households' welfare loss is generally abated for the energy efficiency cases, but the ordinal ranking of the measures is more-or-less the same. Notable exceptions appear with higher EER, reduced infiltration, or LED adoption under *TOU pricing*, where the welfare loss is effectively unchanged. The higher EER efficiency case shows a larger drop in welfare loss when *2018 pricing* is applied than under *TOU pricing*. This is explained by the fact the corresponding behavioral response in *TOU pricing* is a higher thermostat setting.

Improved thermal insulation benefits the most in terms of highest reduction in welfare loss by offering the incentive, and manages to edge out low-e windows under *TOU pricing*. Contrasted to Figure 3, higher EER alone produces a positive welfare change under *2017 pricing*. In the base pricing scenario with the incentives, the combined package of efficiency is preferred.

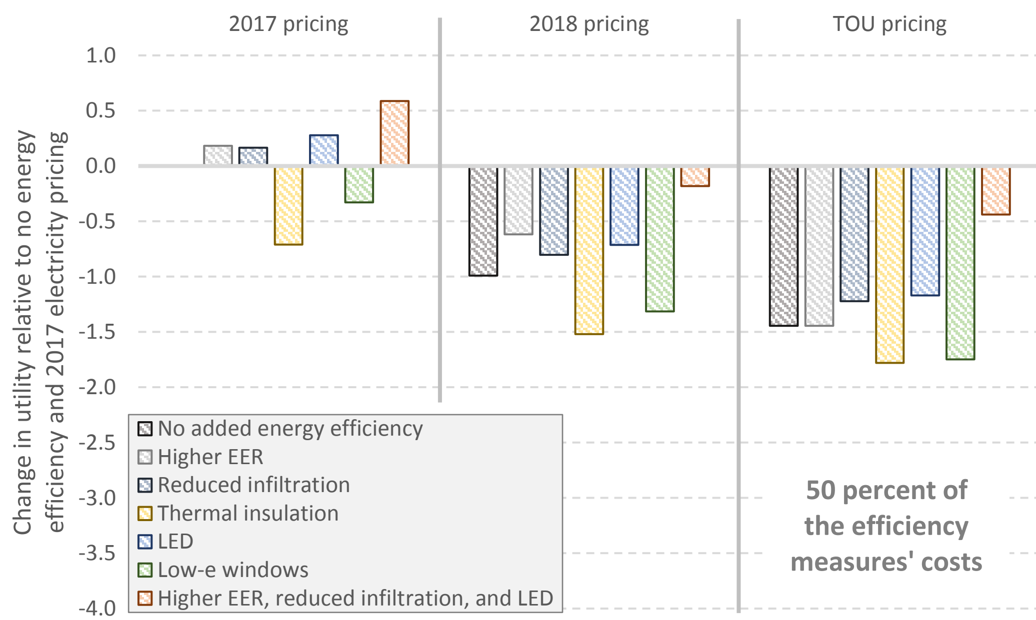

Figure 4 – Effects of the various energy efficiency measures on the welfare of households living in a villa in the central region of Saudi Arabia (incentives amounting to 50 percent of each measure's cost)

Although we show two incentive cases, the incentives required to induce investment differ by region depending on the measures' costs and benefits derived from their local climate and calibrated residential structure, lighting, and air infiltration parameters. This was confirmed by other model runs.

Based on the model results, the least-perceived-cost cases for altering the appliance use schedules never produce a higher utility than the original schedule we stipulate. Although the utility values have minute differences.

Moreover, it is possible to avert the free-rider issue in the analysis by further dividing the physical archetypes into two distinct socio-economic groups; high- and low-income households. We could apply the incentives exclusively to low-income households, who would have budget constraints that do not support the investment costs.

6.2 Energy efficiency adoption versus behavioral response

To investigate whether the model correctly identifies conservation and efficiency as substitutes, we compare the behavioral demand response in model runs with and without monetary incentives. The results suggest that the households' behavioral response to higher electricity prices is dampened with the less expensive energy efficiency. With *TOU pricing*, Figure 2 shows the hourly loads are slightly higher with 50 percent incentives than a case without. Both scenarios apply the same energy efficiency measures (the combined measures case). The differences comes about because of the behavioral response. As the households are spending less on energy efficiency, they have more room in their budgets, and thus they do not exhibit a drastic behavioral response.

In the eastern region in particular, the long-run utility-optimal scenario without incentives yields a thermostat adjustment of 24.5 ^{o}C in the summer. With only half the cost of the efficiency measures paid by the household, the thermostat is adjusted to 23.5 ^{o}C only during the peak hours in the summer.

6.3 The rebound effect

Globally, almost all households' electricity demand is price inelastic in the short-run, and predominantly so in the long-run (Zhu et al, 2018). Our model indicates that long-run price elasticities are highest in the summer months, but still less than unity, thus households always spend more money on electricity as prices rise in our alternative pricing options. We have seen in Table 8 that total electricity consumption falls as electricity prices and/or energy efficiency subsidies rise. Since our modeling framework identifies the levels of electricity use – associated with the combinations of behavioral response and efficiency investment – that maximize utility, we cannot infer that a measure induces direct rebound. For example, we can observe in the model results that when efficiency is subsidized, the household does not have to adjust thermostats as drastically as without incentives; however, we cannot determine if that limited behavioral response hints at a rebound.

Nevertheless, the scenarios allow us to observe the active behavioral decisions with regards the spending on other goods and services. Higher electricity prices cause a rise in budget allocation for electricity, and any fall in total electricity use as a result of efficiency may translate to a rise in the use of other goods and services compared to no added efficiency. Indeed, with 50 percent of the efficiency costs covered for households, their expenditure on other goods and services is lowest when no energy efficiency measure is installed, and highest when the measure that reduces electricity use the most is considered.

This is further exemplified by our results for western Saudi Arabia. With base electricity pricing in the western region, full efficiency costs subsidized, and at the optimal behavioral price response condition, the difference between the lowest (no additional energy efficiency) and highest (all energy efficiency measures installed) expenditures on other goods is 429 dollars per household in the steady-state year. Whereas this difference rises to 760 and 927 dollars in the

2018 pricing and *TOU pricing* cases, respectively. That is 429 to 927 dollars out of 32 thousand dollars of income.

Increasing electricity prices, and the advent of higher efficiency when all of its costs are covered by external parties, create higher household expenditure on other goods and services. Thus, there is an indirect rebound effect on energy demand by the service providers or retailers in meeting the new-found demand for their products. Indirect rebound rises with both behavioral response and energy efficiency allowed, as opposed to doing an analysis of solely energy efficiency.

7. Conclusion

We have introduced and employed a methodology that combines microeconomics and physics to assess households' price-based behavioral demand response and energy efficiency investment. By considering annualized purchase costs, the response we observe from the model's output can be viewed to take place in the long-run. Calibration of the model entailed devising villa, apartment, and traditional house archetypes for four regions within Saudi Arabia.

Three electricity pricing schemes were incorporated to examine how the households may ideally respond: the progressive tariff structures that were in place for households in Saudi Arabia in 2017 and 2018, and a hypothetical time-of-use (TOU) electricity price. The *TOU pricing* case consists of a 15 US cents per kWh during the summer power system peak period, from 12 pm to 5 pm, and a flat 5 US cents per kWh otherwise.

In the base case, where no behavioral response takes place, LED lighting purchases maximize the households' welfare in the long-run. While more aggressive energy efficiency investments are made with the alternative electricity pricing scenarios, there is some behavioral response to the *2018 pricing* structure without incentives, but less subdued than that associated with *TOU pricing*. Households not in the southern region exhibit the most drastic response in the summer, whereas ones in the southern region, who experience a less extreme climate, respond moderately.

Consumers' welfare loss is significantly abated by subsidization of the energy efficiency measures, but the ordinal ranking of the measures is more-or-less the same in the alternative electricity pricing scenarios. The combined measures case still produces the least reduction in welfare in the alternative pricing scenarios. Higher thermal insulation benefits the most from a subsidy in terms of highest reduction in welfare loss.

Additionally, the following notions are observed in this model analysis:

- The possibility for energy efficiency investment lowers the need for conservation at optimal consumer welfare. Consequently, raising monetary incentives that result in less personal expenditure on energy efficiency, households lessen the extent to which they practice conservation.
- As energy efficiency subsidies and electricity prices rise, the difference in spending on other goods and services widens between the highest efficiency case and no added efficiency; the "highest efficiency" case in this paper incorporates an air conditioner with a base 15-BTU/(Wh) EER, reduced infiltration, and LED bulbs. The resulting indirect rebound effect causes a situation where firms would increase their production to meet additional demand.

While only the villa archetypes were used in this analysis, future work will explore the linkage of all the regional archetypes with a model for the energy system; including electric power generators. This analysis helps lay the groundwork for the parameterization that will feed that linkage.

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Appendix A – *Data inputs and model calibration*

The residential electricity use component is calibrated for archetypical villas, apartments, and traditional houses in four regions of Saudi Arabia; the central, southern, western, and eastern areas. Regional weather data sets are consistent with ones used by Matar (2016), and are acquired from the National Renewable Energy Laboratory (NREL) (2017). Information on the construction materials, household size, number of residences and their dimensions, and space heating saturation for each type of dwelling by region is obtained or derived from GAstat (2017a, 2017b). ASHRAE Standard 55-2010 is used to calibrate the acceptable indoor temperature conditions based on ranges for thermal comfort. The thermostat set points that form the calibrated villa stock are 23 ^{o}C, 21 ^{o}C, and 21 to 22 ^{o}C for the summer, spring and fall, and winter, respectively, depending on region. Air conditioner efficiency was estimated by AMAD for Technical Consultation and Laboratories (2011) to be 7 BTU/(Wh) in 2011. While this figure has likely risen since, there is no source that could be referenced.

Appliance use schedules were set as assumptions, as shown in Table A1. The saturation levels of appliances, and their assumed power ratings, are carried over from Matar (2016); that paper also contains data assumptions/inputs not mentioned in this paper. Furthermore, lighting use in the homes by region, and by technology, is input based on the household energy survey by GAstat (2017a). The usage times of indoor lighting are specified such that lights are turned on from sunset to 10 pm. The indoor illumination requirement is set between 130 and 190 lumens per indoor square meter, depending on region, guided by Jefferis and Jefferis (2013). Outdoor lighting only accounts for direct use and does not contribute to the internal heat gain.

Appliance	Times of use on a weekday	Times of use on weekend
Dishwasher	8 pm	
Washing machine	No use	10 am
Dryer	No use	11 am
Stove/oven	11 am and 5 pm	
Water heater	4 am and 8 pm	
Consumer electronics	7 pm to 9 pm	
Refrigerator and freezer	Continuous operation	

Table A1 – Appliance use schedules during the year by weekday and weekend for an archetypical villa (source: author's assumption/result of model calibration)

All the physical constants used to inform such things as the transmittance of heat through windows, the material thermal properties, the fractions of heat gained through radiative and convective means, as well as the trigonometric relationships that govern the solar radiation incident on each outer surface of the house, are derived from McQuiston et al (2005). Weibull distributions of regional and seasonal wind speeds are estimated from the work of Rehman et al (1994).

Since actual load curves for residential customers do not exist, calibration is achieved by aggregating the areas under the resulting load curves, and comparing the values to the actual electricity use values in each region. We show the model values and the actual consumption values in 2017 in Table A2.

Region of Saudi Arabia	Model result (TWh)	Actual data (TWh)	Percentage difference
Western	50.96	49.94	2.1%
Central	45.20	48.19	-6.2%
Southern	15.84	17.31	-8.5%
Eastern	24.76	27.62	-10.3%
Total	**136.77**	**143.05**	**-4.4%**

Table A2 – Model results for combined electricity use of households in villas, apartments, and traditional houses compared against actual data with reference electricity prices (source for actual data: Saudi Arabian Monetary Agency, 2018)

Appendix B – *The results obtained for ϕ_i in the four regions of Saudi Arabia*

Table B1 presents the values for ϕ_{AC} and $\phi_{lighting}$, which are not affected when behavioral response cases are considered. They vary by the efficiency measure installed, regional construction characteristics of villas, and regional climate. As a reminder, adjustment factors are used to reflect the welfare gained by installing the energy efficiency measure(s).

	Western region	**Central region**	**Southern region**	**Eastern region**
No added energy efficiency	ϕ_{AC}= 1.00 $\phi_{lighting}$ = 1.00	ϕ_{AC}= 1.00 $\phi_{lighting}$ = 1.00	ϕ_{AC}= 1.00 $\phi_{lighting}$ = 1.00	ϕ_{AC}= 1.00 $\phi_{lighting}$ = 1.00
Higher EER	ϕ_{AC}= 1.90 $\phi_{lighting}$ = 1.00	ϕ_{AC}=2.14 $\phi_{lighting}$ = 1.00	ϕ_{AC}= 2.50 $\phi_{lighting}$ = 1.00	ϕ_{AC}= 2.14 $\phi_{lighting}$ = 1.00
Reduced infiltration	ϕ_{AC}= 1.28 $\phi_{lighting}$ = 1.00	ϕ_{AC}= 1.18 $\phi_{lighting}$ = 1.00	ϕ_{AC}= 1.12 $\phi_{lighting}$ = 1.00	ϕ_{AC}= 1.20 $\phi_{lighting}$ = 1.00
Thermal insulation	ϕ_{AC}= 1.68 $\phi_{lighting}$ = 1.00	ϕ_{AC}= 2.16 $\phi_{lighting}$ = 1.00	ϕ_{AC}=2.76 $\phi_{lighting}$ = 1.00	ϕ_{AC}= 2.21 $\phi_{lighting}$ = 1.00
LED	ϕ_{AC}= 1.00 $\phi_{lighting}$ = 15.00	ϕ_{AC}= 1.01 $\phi_{lighting}$ = 12.63	ϕ_{AC}= 1.01 $\phi_{lighting}$ = 13.91	ϕ_{AC}= 1.00 $\phi_{lighting}$ =14.42
Low-e windows	ϕ_{AC}= 1.03 $\phi_{lighting}$ = 1.00	ϕ_{AC}=1.02 $\phi_{lighting}$ =1.00	ϕ_{AC}= 0.99 $\phi_{lighting}$ = 1.00	ϕ_{AC}= 1.02 $\phi_{lighting}$ = 1.00
Higher EER, reduced infiltration, and LED	ϕ_{AC}= 2.46 $\phi_{lighting}$ = 15.00	ϕ_{AC}= 2.54 $\phi_{lighting}$ =12.63	ϕ_{AC}= 2.82 $\phi_{lighting}$ = 13.91	ϕ_{AC}= 2.58 $\phi_{lighting}$ =14.42

Table B1 – Model results for the adjustment factors, ϕ_i. The details of each energy efficiency case are mentioned in Section 4.2.