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Residential Energy Efficiency Investment and Demand Response Under Different Electricity Pricing Schemes: A Physical-Microeconomic Approach

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Abstract

This paper expands on a previously presented methodology that merges the physical properties of energy with microeconomic principles: The physical side of the model informs how much electricity is used to satisfy services that people desire, while the microeconomic side imposes a utility function to represent household satisfaction. This paper adds energy efficiency investment to the price-based behavioral demand response and presents results representative of the long-run steady-state. It examines several electricity pricing schemes and energy efficiency options, with the costs and benefits of each option explicitly modeled in the physical representation.

Two key insights are derived from performing a modeling analysis for archetypical villas across Saudi Arabia:

- Energy efficiency investment lowers the need for energy conservation. Raising energy efficiency subsidies causes households to reduce their energy 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.

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. Goldman et al. (2010) discuss how energy efficiency and behavioral price-based demand responses can overlap. Although they state that updating building codes would lessen the need for behavioral response, they mention two other types of coordination: combined awareness campaigns and market-driven services. Energy service companies, or ESCOs, offer market-driven services, which serve customers who are seeking lower energy costs.

Behavioral change alone can be exercised relatively quickly, so its effect dominates demand response in the short-run. Investments in energy efficiency measures, however, require time to materialize due to many reasons, including a lack of capital or households seeing existing appliances through their economic lifetimes. Plus, energy efficiency measures differ in their monetary cost, the inconvenience of their 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. Analyzing energy efficiency investment against energy price changes would therefore indicate the 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. In this case, econometric estimates are not indicative of the response warranted by new pricing policies. Matar (2018, 2019) explored how a household would alter its expenditure among different goods and services in response to a change in the electricity pricing scheme. The household could not make energy efficiency purchases.

Paatero and Lund (2006) apply a behavioral modeling framework to the electricity consumption of 10,000 dwellings. The households they study do not exhibit space heating or cooling power loads. Therefore, the authors do not rely on physical properties to ascertain electricity use; they utilize statistical data to populate their model.

Furthermore, 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 formulation of a utility-maximization problem is articulated 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 is 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 incorporating 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:

> To incorporate energy efficiency purchases in the hybrid economic-physical construct used by Matar (2018, 2019).

> Secondly, use this framework to analyze the effects of electricity price changes on household decisions. Households are a heterogeneous population. However, this analysis extracts some general insights regarding the role of behavioral price response and energy efficiency investment, and the effects of monetary aid to remedy any investment costs.

This paper is structured as follows: The next section reviews the recent literature on energy efficiency, the rebound effect, and their relationship to energy prices. The subsequent section outlines the approach of this paper's analysis, followed by the electricity prices it considers. It concludes with a presentation and discussion of the results.

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 the 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 than optimal demand-side investment based on their production costs and thus would be required 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 United States (U.S.) have resulted in cost savings of 1.6 to 3.3 U.S. cents per kilowatthour (kWh). These savings show that energy efficiency is cost effective compared to the marginal cost to the power generators of supplying electricity. This is almost universally the case, except for generators that receive fuel at low administered prices. For example, some Gulf Cooperation Council (GCC) countries 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 that incentivized energy efficiency may have slightly raised the likelihood of investment in it. Although the programs had 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; they provide evidence that households in Italy who were not going to invest in energy efficiency would be more likely to do so if they were offered rebates.

A 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 providing feedback on usage to consumers. Energy certificates accompany consumer appliances that assist customers in making purchasing decisions. The authors found that feedback and labels were more effective than energy audits in diminishing this market failure; however, they found that the impact of energy audits was mixed. In-home displays showing energy use before and after the implementation of energy efficiency measures provide similar information to an energy audit or feedback.

There is also a wide body of literature that suggests there could be a 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) note that the literature has predominantly analyzed this issue using 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 finding ties into this 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 for it, they may spend more on other goods. Doing so would result in additional energy consumption for the production of these goods. 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 the indirect rebound effect, and that analyses have generally addressed it in the context of lower energy prices, as opposed to rising disposable incomes. This paper investigates if the results indicate the presence of indirect rebound from higher disposable incomes by examining household expenditures.

Moreover, if households paid real-time prices for electricity, the price would fall if their power demand fell as a result of conservation and/or efficiency measures. This is because, as demand falls, the equilibrium point may shift down the supply curve as the operation of more expensive marginal power generators reduces. 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, and
- lowers the average electricity price paid.

This is not universally true, 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.

Electricity pricing is administered in China (Yang et al., 2018). Lin and Liu (2013) show that if energy efficiency measures in Chinese households are coupled with higher electricity prices and associated investment costs, the direct rebound effect could be negligible, if not negative (as prices keep rising). Because energy efficiency is typically adopted by environmentally conscious households or in response to higher energy prices, we would expect a minimal direct rebound, particularly if the household bears the investment. GCC countries also administer fixed electricity prices, illustrated by the prices for electricity in Saudi Arabia in a subsequent section.

Technology Adoption by Households

This paper presents the long-run end state of electricity price response. Previous research reveals that the adoption of new technology by households is not instantaneous. It takes years for a heterogeneous population to replace their existing stock of appliances or equipment; especially if the technology is new and future cost (and price) reductions are expected. Technology adoption is characterized by an S-shaped curve ("the diffusion curve" hereafter) (Jaffe et al. 2004). Adoption is typically slow at the beginning and end of this curve, with the in-between years exhibiting a large uptake. Of course, we can hypothesize that the shape of this curve differs from one energy efficiency measure to another. This depends on their up-front prices, 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 to model 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 the full adoption of light-emitting diodes (LEDs), although the banishment of incandescent lights resulted in the highest adoption of LEDs. Their diffusion curves were mostly characterized by lower positive slopes than one would expect from an S-curve. Friege (2016) also uses an ABM to analyze 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 10-year period. None of the studies reviewed assessed the effects of price-induced energy efficiency investment.

Methodology and Data Input

Residential electricity use model

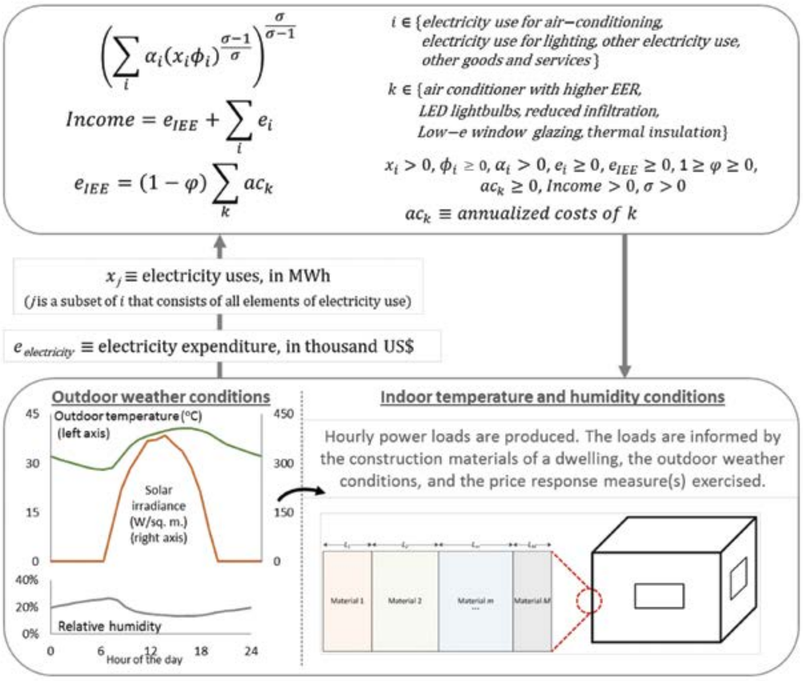
Matar (2018, 2019) proposes a linkage between a physical building energy model and a household whose decisions are consistent with microeconomic fundamentals. Previous analyses explored demand response measures as a result of different electricity pricing schemes, examining the demand response measures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

This paper extends that model to include the purchase of energy efficiency measures. In addition to applying different electricity pricing schemes and behavioral demand responses, such as adjusting the thermostat in the summer or the spring and fall, this paper assesses how those different prices influence energy efficiency adoption. The model is also expanded to represent archetypes of villas in multiple regions of Saudi Arabia. The regional breakdown takes the Saudi Electricity Company's (SEC's) operating areas: southern, western, central, and eastern. The regional dimension considers the climatic differences across the country and their differing energy efficiency needs.

Appendix A contains the data calibration of the physical component. As the appendix and this section detail, the model is calibrated for regional archetypal villas, apartments, and traditional houses to match the actual electricity use data in 2017. This paper analyzes the villas in all four regions to ensure consistency with 2017 data.

Figure 1 illustrates the coupling of the two components. In this linkage, the households are assumed to 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 this analysis ultimately identifies the point at which the utility is maximal, it does not strictly maximize it in the optimization problem sense. The analysis only computes its value for all possible combinations of price response measures and energy efficiency adoption, assuming a budget constraint and that households would have the same utility functional form.

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



Note: MWh= megawatthour; °C= degrees Celsius; EER= energy efficiency ratio; W= Watts; sq. m.= square meter

Source: KAPSARC analysis.

Past analyses using this framework employed a Cobb-Douglas functional form. Although this study does not necessarily optimize directly, it applies a more flexible function. 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 megawatthours (MWh), and ϕ_i are adjustment factors that estimate the utility gained by the installation of energy efficiency measures. In other words, ϕ_i adjust any decreased use of electricity due to energy efficiency by raising x_i ϕ_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.

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

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

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

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

$P_{AC_{season,hour,daytype}}$ are the hourly loads for the heating, ventilation, and air conditioning (HVAC) system by season and day type. The analysis considers two types of day: weekends/holidays and weekdays. Similarly, $P_{lighting_{season,hour,daytype}}$ 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 the 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, affect the cooling loads in dwellings (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 s. Each set of values for any scenario is related to the initial state, $(\cdot)_{\text{initial}}$.

In Equation 6, the power needed to meet the initial

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

$$\phi_{lighting} = \frac{N_{initial}}{N} \quad (6)$$

α_i are the preferences, and they sum to unity for all i. The households were calibrated to have preference shares for electricity ranging between 5% and 7%, depending on the 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. The preference share devoted to electricity is further disaggregated to its various components. The analysis uses 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 100% minus the electricity preference share. Finally, σ is the elasticity of substitution, and the calibrated value is 0.9.

Table 1. Estimated electricity use breakdown for a household in Saudi Arabia.

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

Source: estimated by the author from Faruqui et al. (2011).

To calculate $x_{other\ electricity}$, electricity used for 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 (CDSI 2013). e_i are the expenditures on electricity and other goods and services. Expenditure on electricity may be computed based on hourly prices or Saudi Arabia's present progressive pricing structure. e_{IEE} is the annualized investment and maintenance cost required for a particular energy efficiency measure. The analysis only includes the expenditure on higher energy efficiency measures in the income constraint, as its effects in the form of lower electricity use appear in the utility function.

$$\text{Income} = e_{IEE} + \sum_i e_i$$

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 measures 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 which would result in optimal avoided costs is referred to as the 'energy efficiency gap.'

Thus, the analysis includes a coefficient in Equation 8 that reduces 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.

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

ac_k are the annualized costs of the energy efficiency options, k, defined in the next subsection. 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. The analysis shows how the model solution differs for several values of φ. To circumvent the issue of free-riders, who would invest in energy efficiency anyway, policymakers could allocate subsidies to only those households whose annual incomes fall below the median level of each region. Operationally, this means that a single physical archetype is split into two versions that differentiate between income levels. Due to a lack of income distribution data, this paper only mentions the possibility of accounting for free-riders. Hence, the analysis incorporates a non-zero φ for all households.

Table 2. Annual household income in Saudi Arabia by region.

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

Source: CDSI (2013).

This analysis also incorporates the appliance shifting algorithm used by Matar (2017). The analysis summarizes the appliance usage approach here, although more detail is provided in Matar (2017). 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), the assumption here is that households may consider both the cost of electricity and a non-monetary cost of inconvenience when shifting the use of appliances. This sum of the two cost components is termed the 'total perceived cost.' This analysis assumes that households are provided with electricity prices sufficiently in advance, and thus have time to react accordingly and minimize the total perceived cost of their appliance use. The cost of inconvenience increases more rapidly the further away in time the use of an appliance is shifted.

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

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 (weekdays/weekends) (d) and region (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 turned 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 this analysis. γ_{inconv} denotes the rate of increased costs to the household by shifting their use of an appliance further away from its original time of use. This is estimated by the authors to be US$10 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 away in time households shift their use. Thus, households 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.

Energy efficiency adoption

As shown in Table 3, this analysis considers 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 array of infinitely possible choices. This analysis examines a subjectively-defined set of efficiency choices. Other analysts may wish to consider alternative definitions. The options are upgrading air conditioners from an average energy efficiency ratio (EER) from the calibration value to 15 British thermal units (Btu) per Watthour (Wh), sealing any cracks between doors or windows and walls in the thermal envelope, investing in low-emissivity (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.

In the calibrated case, all households are estimated to have an infiltration rate of 0.65 to 0.80 air changes per hour (ACH), depending on the region. The 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% of traditional houses are built using adobe, or mudbricks. The remaining 35% of traditional houses are made of concrete. However, this analysis takes the 65% majority to represent a single archetype and to 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.

Each efficiency option has a purchase cost that is annualized over its designed life using a discount rate of 30%. This is in line with Harrison et al. (2002) and Enzler et al. (2014), who report an average discount rate of 28% for individuals in Denmark and estimate an even higher value for Switzerland. This effectively means households who discount at 30% are impatient relative to those with lower values and patient relative to those with higher values. Purchases are estimated to not increase the operation and maintenance costs over the base case.

Table 3. Combination of analyzed price-base demand responses and energy efficiency measures.

Energy efficiency cases	**Demand response measures**			
	Thermostat set-point adjustments			
	Summer, spring, and fall	**Additional adjustment during the peak in the summer**	**Turning off lights**	**Appliance load shifting**
Without higher energy efficiency	Incrementally raising the set-point from 0°C to 3°C in the summer, or from 0°C to 1.5°C in the spring and fall.	The household has the option to raise the thermostat set-point further from the summer setting by 0.5°C	Incrementally lower the lighting requirement in the dwelling.	The household may shift its appliance use based on their perceived costs, which is the sum of the monetary cost and the cost of inconvenience.
Air conditioning with an average EER of 15 Btu/(Wh)				
Reduced infiltration to 0.30 ACH				
Low-e windows				
More stringent thermal insulation (apartments and villas only)				
100% LED adoption				
The combination of higher EER, sealing cracks and LED adoption				

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

	Materials of walls and roof, from the exterior surface (top) to the 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]

The costs used in this analysis are summarized in Table 5. For the scenario where measures are combined, the associated measures' costs are aggregated.

The levels of thermal insulation, reduced infiltration, and/or how much heat is gained through the windows will affect the maximum cooling load [max(Q̇_cooling)] that a household experiences throughout the year. This 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. The air conditioning unit cost is assumed to include the cost of installation.

ε stands for LED bulb efficacy in lumens per W; r is the power rating of the bulb; TFA is the total indoor floor area of the residence; I is the illumination required, which changes based on energy conservation; ESA is the total area of the walls and roof; TGA is the total glazing area; $L_{(\cdot)}$ are the labor costs for installing air conditioners, windows, or thermal insulation, and $c_{(\cdot)}$ are the costs per unit for each efficiency measure. $c_{(\cdot)}$ are in US$ per Btu of capacity for air conditioners, US$ per lightbulb for LEDs, and US$ 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 no sources could be found to reference, L_{AC}, L_{window}, and $L_{thinsul}$ are estimated to be US$500, US$1,000, and US$10,000, respectively.

For example, the full costs of the more efficient air conditioner when only air conditioners are adopted are calculated to be US$1,619, US$3,028, US$3,126, and US$3,541 per household in the southern, western, central, and eastern regions of Saudi Arabia, respectively, depending on the regional climate.

Table 5. Full purchase costs of energy efficiency measures (US$).

Energy efficiency measure	Full purchase cost (US$ per household)
Air conditioners with average EER of 15 Btu/Wh	$c_{AC} \cdot \max(\dot{Q}_{cooling}) \cdot dt + L_{AC}$
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	$\frac{c_{LED} \cdot I \cdot TFA}{\varepsilon \cdot r}$

Source: Author's estimates based on Austrotherm Insulation (2017) for thermal insulation, and online retailers for the rest.

Note: c_{AC}=6.9 U.S. cents per Btu of capacity; c_{seal}=US$2.15 per m^2; c_{window}=US$211 per m^2; $c_{thinsul}$=US$10 per m^2; c_{LED}=US$2.15 per bulb.

The full costs of low-e windows are dependent on the dwelling size and range between US$3,665 and US$4,806 for all regions. Selecting any combination of these energy efficiency cases will change 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. This will 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 a lack of information available to households about energy efficiency measures, 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) associated costs related to buying 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.

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. This analysis examines 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 than 2 MWh, it paid 1.33 U.S. 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 country's electricity tariffs on January 1, 2018, for the consumption brackets below 6 MWh per billing period. This pricing policy is still active in 2019. Although the government introduced a program to compensate households based on their income (Citizen Account Program 2018), this analysis does not distinguish households by income level. This scenario is titled "2018 pricing."

> A time-of-use (TOU) price that stipulates a flat tariff of 5 U.S. cents per kWh is charged throughout the year, except for the summer during the system peak hours. Then, a 15-U.S. cents-per-kWh charge is imposed. This scenario is titled "TOU pricing."

Matar (2018) details the computation of the total electricity cost; the model can aggregate the electricity costs whatever the pricing scheme applied. This analysis could have adopted a real-time pricing scheme had it analyzed apartments and traditional houses and linked the framework with a supply-side power system model. Then, the marginal cost of electricity generation and transmission would have been 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.

Saudi government agencies have applied energy efficiency labels, stricter minimum standards for air conditioners and thermal insulation, and financial

Table 6. Household electricity pricing from 2016 until 2019.

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

Sources: ECRA (2016, 2018).

support for efficiency purchases. Many of these 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 customers of the appliances' energy use characteristics. The 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 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.

Table 7. TOU electricity price scheme used in this analysis.

Time of year	TOU electricity price scheme (U.S. cents per kWh)
Summer months during peak hours (from 12 p.m. to 5 p.m.)	15.00
Outside of summer peak hours, including all other seasons	5.00

Source: Author's assumptions.

Results and Discussion

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 this paper's modeling approach considers the impact of investments 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 an 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.

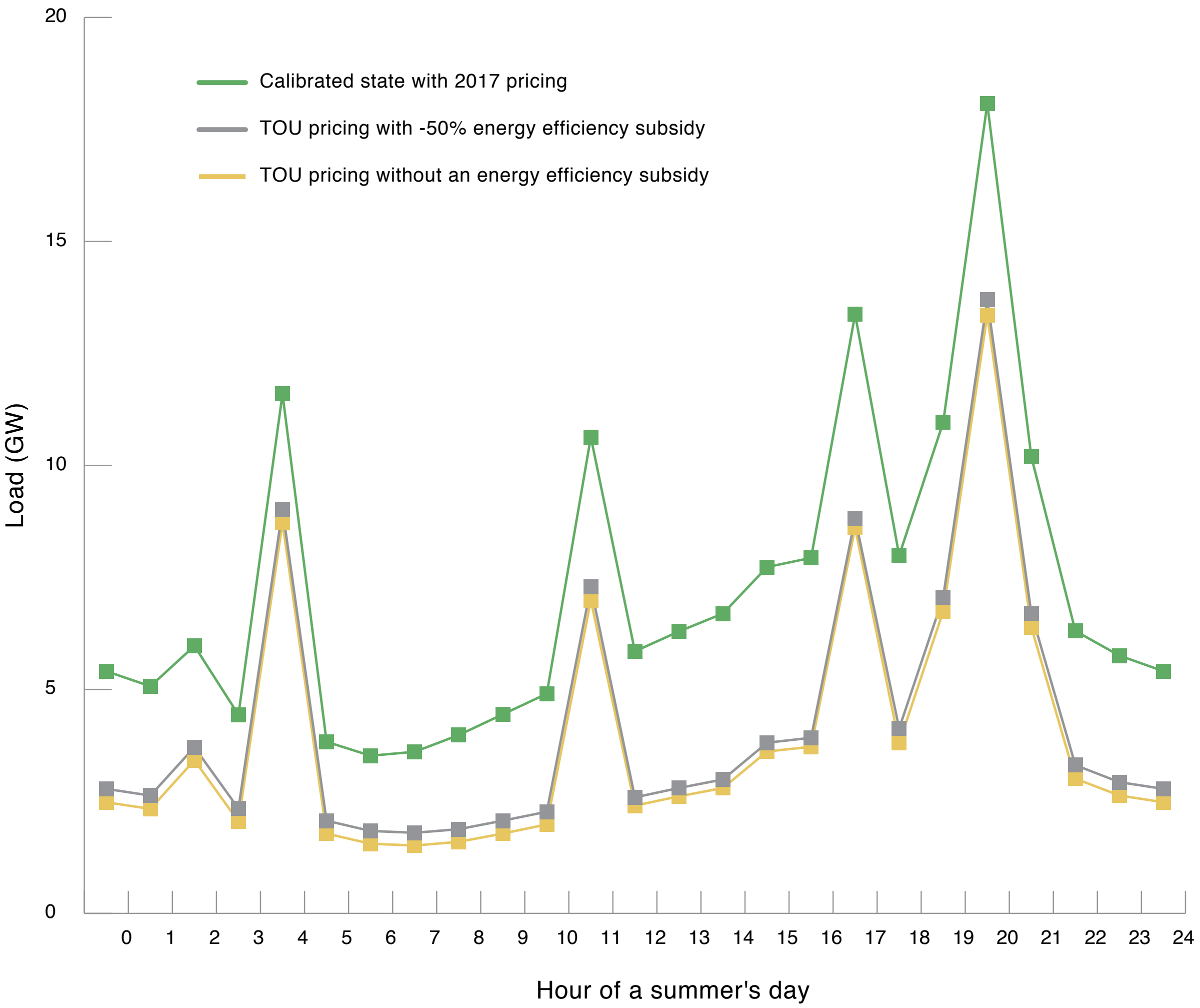
There is a small energy efficiency investment in the base case. There are some efficiency cases, like the adoption of LED lighting and sealing cracks around the dwelling, which yield greater cost effectiveness in the long run. In the long run, the annualized costs of these measures pale in comparison to the realized benefits of reduced electricity expenditure. 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 need for cooling in the summer. Figure 2 shows the hourly load curves in the summer for some of the scenarios. The spikes reflect the author's assumption of the appliance use schedule.

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 regions except for the southern region also moderately adjust their thermostats in the summer by 1.5°C with 2018 pricing, because 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. The modeled thermostat in the peak hours during the summer is raised by an additional 0.5°C with TOU pricing applied.

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

		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

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



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 ratio of costs to the electricity reduction of LED bulbs is more attractive than incandescent bulbs (the status quo). This is shown in Figure 3 for the central region, where the LED efficiency scenario maximizes the archetypical household's utility at the optimal behavioral state compared to no additional energy efficiency measures. Although higher air conditioner efficiency would produce lower utility, just installing them with LED bulbs and reduced infiltration would yield greater benefits than doing nothing.

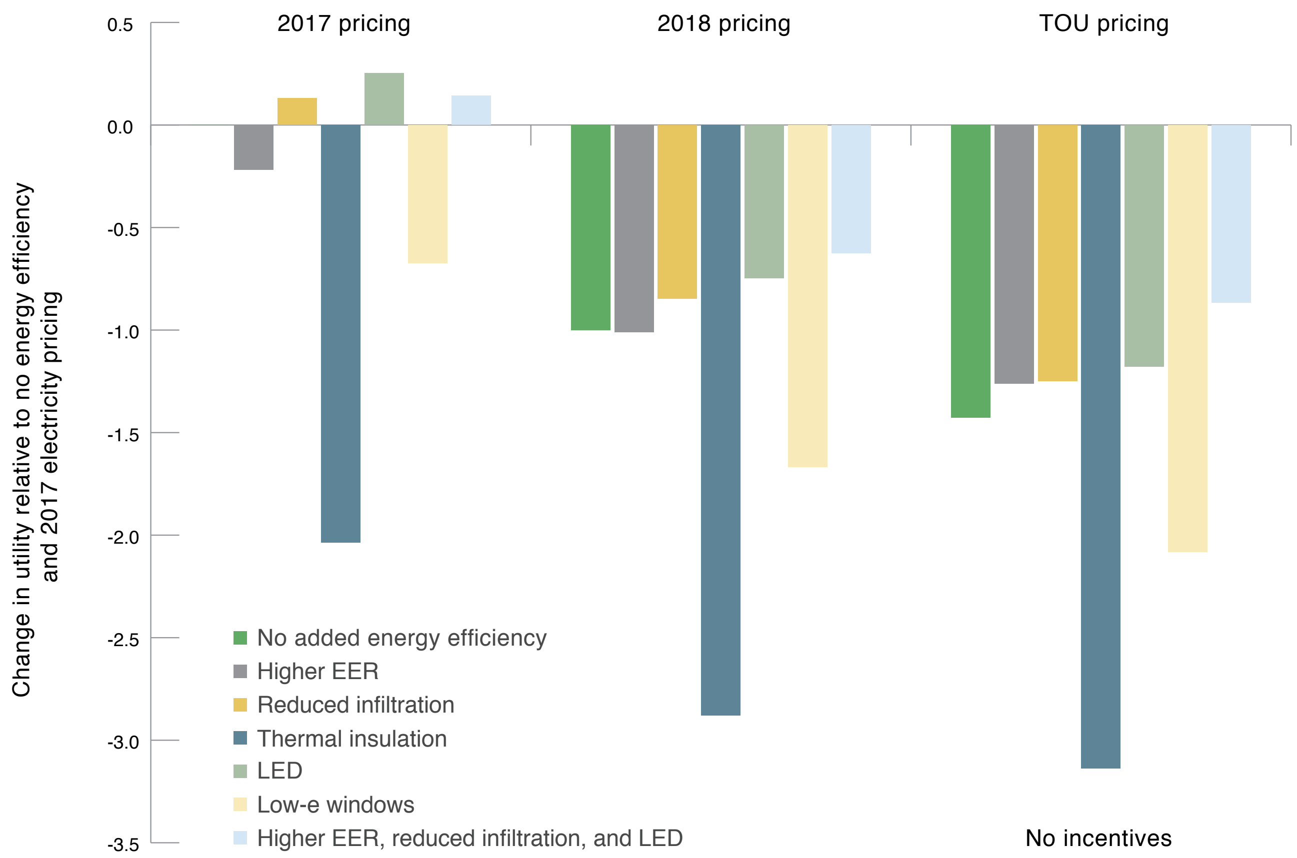
In the alternative electricity pricing schemes, the combination of higher EER, reduced infiltration, and LEDs maximizes the utility relative to the 2017 pricing and no added energy efficiency. Raising electricity prices and practicing conservation alone yields lower consumer welfare than if this were to be coupled with efficiency purchases.

The change in utility associated with the packaged energy efficiency measures is not derived from the utility changes of any one measure implemented. The 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 non-linear marginal benefit gained by installing energy efficiency. We see, for example, that the effect on the households' welfare of just installing more efficient air conditioners differs from installing them along with other energy efficiency measures.

Figure 4 shows that the consumers' efficiency choice is not affected by the offer of a 50% subsidy. Households' welfare losses are generally abated for the energy efficiency cases, but the ordinal ranking of the measures is more or less the same. The combined measures case still yields the least reduction in welfare in the alternative pricing scenarios. 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.

Under TOU pricing and by offering the subsidy, the highest reduction in welfare loss to households is exhibited by improved thermal insulation, above that of low-e windows. Compared with 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 by the household.

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



Source: KAPSARC analysis.

Although only two incentive cases are shown, 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.

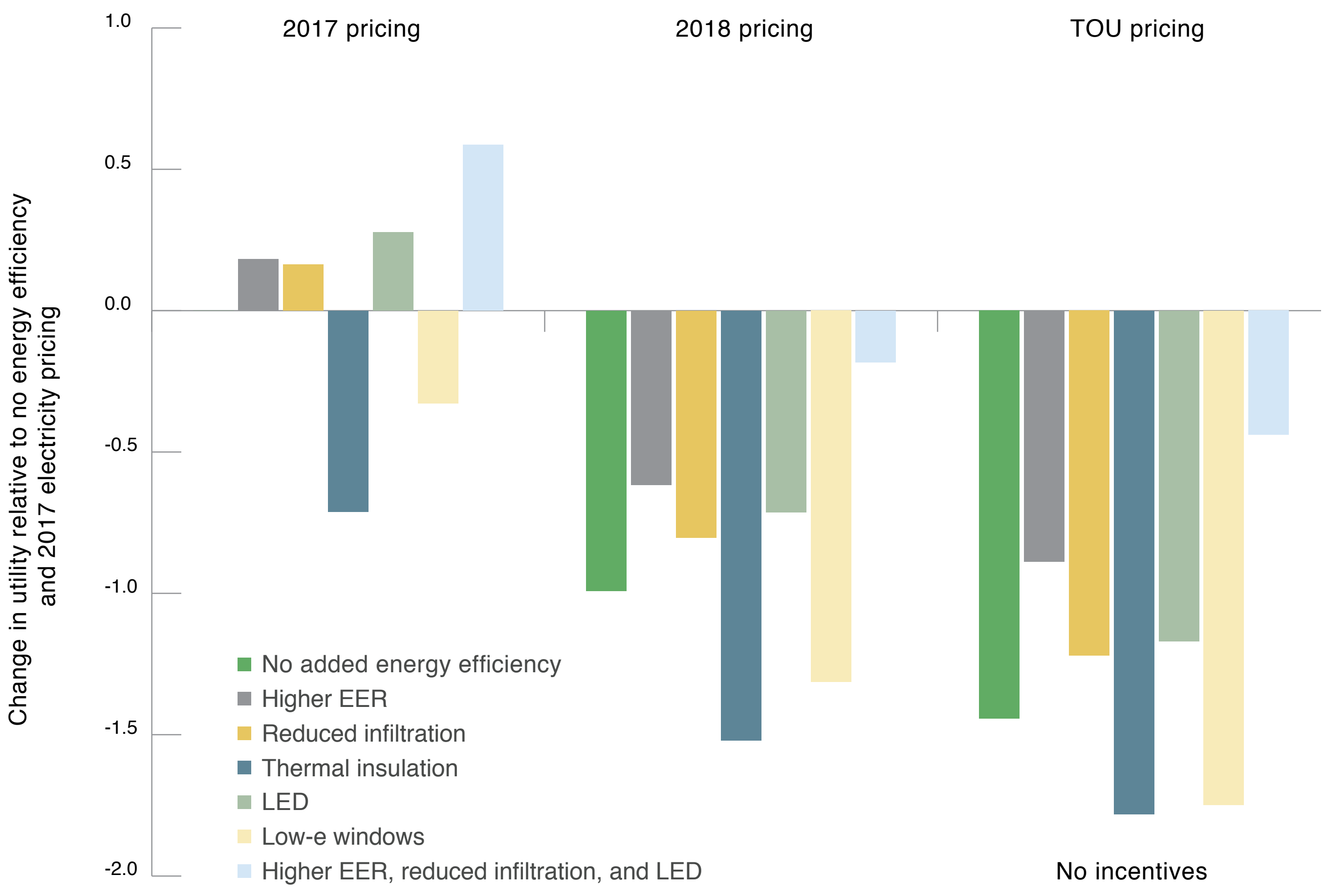
Based on the model's results, the least-perceived-cost cases for altering the appliance use schedules never produce a higher utility than the original schedule stipulated. However, the utility values have minute differences.

It is possible to avert the free-rider issue in the analysis by further dividing the physical archetypes into two distinct socioeconomic groups: high- and low-income households. The incentives could be applied exclusively to low-income households, who would have budget constraints that do not support the investment costs.

Energy efficiency adoption and behavioral response

To investigate whether the model correctly identifies conservation and efficiency as substitutes, this

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



Source: KAPSARC analysis.

paper compares 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 by the less expensive energy efficiency measures. Figure 2 shows that with TOU pricing, the hourly loads are slightly higher with 50% subsidies than without. Both scenarios apply the same energy efficiency measures (the combined measures case). The difference arises from the behavioral response. Households have larger budgets as they are spending less on energy efficiency, and thus they do not exhibit significant behavioral response.

In the eastern region, in particular, the long-run utility-optimal scenario without incentives yields a thermostat adjustment to 24.5^{o}C in the summer. With 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 of the summer.

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). This paper's model indicates that long-run price elasticities are highest in the summer months, but still less than unity. The alternative pricing options included in this analysis show that households always spend more money on electricity as electricity prices rise. We have seen in Table 8 that total electricity consumption falls as electricity prices and/or energy efficiency subsidies rise. Since this paper's modeling framework identifies the levels of electricity use – associated with behavioral responses and efficiency investments – that maximize utility, it cannot be inferred that any one energy efficiency measure induces a direct rebound. For example, the model results show that when efficiency is subsidized, the household does not have to adjust its thermostats as drastically as it would without incentives. However, it is not possible to determine whether this limited behavioral response is a rebound effect.

Nevertheless, the scenarios allow us to observe active behavioral decisions regarding households' spending on other goods and services. Higher electricity prices cause a rise in budget allocations for electricity, and any fall in total electricity use as a result of energy efficiency measures may cause a rise in the purchase of other goods and services compared to no added efficiency. Indeed, with 50% of the efficiency costs for households subsidized, 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 installed.

This is further highlighted by this paper's results for western Saudi Arabia. With base electricity pricing, fully subsidized efficiency costs, 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 US$429 per household in the steady-state year. Whereas this difference rises to US$760 and US$927 in the 2018 pricing and TOU pricing cases, respectively. That is US$429 to US$927 out of the average household's income of US$32,000.

Increasing electricity prices and installing higher efficiency, with all costs to the household covered by external parties, results in higher household expenditure on other goods and services. Thus, service providers and retailers experience an indirect rebound effect from reduced energy demand by selling more goods and services. This indirect rebound is evident when jointly analyzing behavioral responses and energy efficiency measures, as opposed to solely analyzing the impact of energy efficiency measures.

Conclusion

This paper has 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 observed from the model's output can be viewed as a long-run response. Calibrating the model entailed devising an archetypal villa, apartment, and traditional house for four regions within Saudi Arabia.

Three electricity pricing schemes were incorporated to examine how households may 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 15 U.S. cents per kWh during the summer power system peak period, from 12 p.m. to 5 p.m., and a flat 5 U.S. 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. More aggressive energy efficiency investments are made in the alternative electricity pricing scenarios. There is still some behavioral response to 2018 pricing and TOU pricing without incentives, although it is more pronounced in the TOU pricing scenario. Households not in the southern region exhibit the most significant response in the summer, whereas those in the southern region who experience a less extreme climate respond more moderately.

Consumers' welfare loss is significantly abated by subsidies for energy efficiency measures, while 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. Subsidies for higher thermal insulation produce the highest reduction in welfare loss.

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

> Energy efficiency investment lowers the need for conservation while maintaining optimal consumer welfare. Consequently, if more subsidies are provided for energy efficiency measures, households will limit their energy conservation.

> As energy efficiency subsidies and electricity prices rise, the difference in spending on other goods and services increases. This is seen in the contrast between the highest efficiency case and the case with no added efficiency. The highest efficiency case in this paper incorporates an air conditioner with a base of 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.

Future work will extend to cover all regional archetypes. The residential model will also be linked with an energy system model to cover the supply side of energy. 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, as defined by the SEC: central, southern, western, and eastern areas. Regional weather data sets are consistent with those 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 in the calibrated villa stock are 23°C, 21°C, and 21°C to 22°C for summer, spring and fall, and winter, respectively. 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, no source could be found to determine whether this has happened.

Appliance use schedules were set as assumptions (Table A.1). The saturation levels of appliances and their assumed power ratings are adopted from Matar (2016), which 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 p.m. The indoor illumination requirement is set between 130 and 190 lumens per indoor square meter, depending on the region, after Jefferis and Jefferis (2013). Outdoor lighting only accounts for direct use and does not contribute to the internal heat gain.

Table A.1 Appliance use schedules during the year by weekday and weekend for an archetypal villa.

Appliance	Times of use on weekdays	Times of use on weekends
Dishwasher	8 p.m.	
Washing machine	No use	10 a.m.
Dryer	No use	11 a.m.
Stove/oven	11 a.m. and 5 p.m.	
Water heater	4 a.m. and 8 p.m.	
Consumer electronics	7 p.m. to 9 p.m.	
Refrigerator and freezer	Continuous operation	

Source: Author’s assumption/result of model calibration.

Appendix A – Data inputs and 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. Table A.2 shows the model values and the actual consumption values in 2017.

Table A.2 Model results for the combined electricity use of households in villas, apartments, and traditional houses compared with actual data using reference electricity prices.

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%**

Source for actual data: SAMA (2018).

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

Table B.1 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 climates. As a reminder, adjustment factors are used to reflect the welfare gains of installing the energy efficiency measure(s).

Table B.1 Model results for the adjustment factors, ϕ_i. The details of each energy efficiency case are given in section 4.2.

	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 LEDs	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

About the Author

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Walid is a research fellow at KAPSARC working on energy systems models, including the KAPSARC Energy Model, and satellite projects such as KAPSARC's residential electricity use model. Walid holds a Master of Science degree in mechanical engineering from North Carolina State University, and a Bachelor of Science degree in the same field from the University of South Carolina.

About the Project

This project aims to develop a framework to analyze households' price responses to any electricity pricing scheme, especially in regions where statistical data are unavailable or insufficient. The framework combines physical and microeconomic principles. The physical side governs electricity use throughout the day, while the microeconomic side imposes a normative utility function for the household, to represent its satisfaction.

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