Can a Daily Electricity Bill Unlock Energy Efficiency?

Evidence from Texas

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1. Introduction

1.1 The Study

Electricity expenses for residential customers can be a substantial portion of their disposable income, particularly in areas of the country where lifestyle and comfort demand significant electricity usage. In Texas, with long hot summers and high humidity in the big population centers of Houston and Dallas, the annual electricity usage tends to be higher than other parts of the country, averaging about 15,000 kilowatt-hours for a residential home. Further, according the most recent residential household survey by the EIA, the annual electricity cost for an average U.S. household is about $1,801/year (EIA, 2009) that is approximately 5% of an annual per capita income.[1] Given the significant expense, electricity customers prefer to be able to manage their electricity usage to save energy and money (Alcott and Greenstone, 2012). But, it can be difficult for customers to understand their usage and make effective decisions.

One reason it can be difficult is that customers do not have timely access to information on their usage and spending. In fact, most electric utilities bill customers far after their usage, and any irregular usage due to changes in weather, appliance demand, and other factors are long-forgotten. This system, where customers use electricity in one month and receive a bill sometime in the following month (often followed by another lengthy period before the payment is due) provides infrequent usage information and no payment and usage linkage. This is especially true historically as the analog meter infrastructure provided only a single data point for around 30 days of consumption. For the purpose of this study, we call this traditional structure a Monthly Billed Energy Service ("MBES"). Under an MBES, customers have little insight into their usage and cannot easily associate the costs of that usage with the ultimate benefits they receive. This lack of transparency unsurprisingly causes customers to not understand or control their energy usage to eliminate inefficiency.

Over the past few years, three key technological and market changes have provided the opportunity for a new product to be offered to electricity consumers. The first change is the wide-scale proliferation of digital meters, which can measure consumption on intervals smaller than a month (often as frequently as 15 minutes), relay the usage information daily (or more often) to a central metering and billing system, and allow local distribution utilities to remotely and quickly

[1] Annual per capita disposable personal income in Texas from 1990 to 2016 (in US Dollars) listed in here.

disconnect and reconnect service. The second change is the ongoing trend of consumers deriving benefits from prepaid offerings in other areas of their lives, such as prepaid debit cards and prepaid cellular service. The third change is the ability to communicate important information with customers through robust and secure digital channels, like email and text messaging. These changes together allow energy suppliers to offer a Daily Billed Energy Service ("DBES") which is commonly known as "prepaid electricity."

DBES addresses some of the problems of transparency that currently plague MBES. DBES gives consumers many more touchpoints on their electricity usage which can empower them to make more informed decisions.[2] Customers using DBES don't only get more frequent insight into usage but undertake a complete transaction every day by having a complete bill presented, including their usage, and making a payment to continue service. Providing information is important, but a daily transaction is an effect beyond information presentation. As such, many believe that DBES could become widely used by consumers (DEFG, 2015; Navigant Research 2016).

In this study, we analyzed energy efficiency impacts of a DBES offered by Direct Energy in Texas using 15-minute interval customer usage data from the three years 2014, 2015, and 2016.[3] Because various DBES products can operate differently, we will discuss the Direct Energy product in particular.

Previous studies have also quantified the effectiveness of prepaid products for energy efficiency. A study of the Salt River Project's prepay product M-Power found efficiency of about 12% (Qiu and Xing, Arizona State and SRP, 2015). A 2014 study of prepay customers in two Pacific Northwest cooperatives found 5.5% and 14% efficiency (Integral Analytics for NEEA and DEFG, January 2014). And a study of Oklahoma Electric Cooperative concluded an 11% efficiency (Ozog, Integral Analytics, 2013). These studies have cited as reasons for the energy efficiency benefit to be (1) better information through more frequent communications, (2) more engagement with energy consumption choices, (3) reduction in hyperbolic discounting of energy costs, and (4) the desire to avoid cost and inconvenience of disconnection.

[2] MBES customers can also see their detailed consumption data through their supplier's website or smartmetertexas.com. Because these are pull channels, however, recurring participation by customers is very low.
[3] For more information on Direct Energy, please visit www.directenergy.com.

No known studies have examined the Texas markets. Texas is a particularly important region to examine for energy efficiency because the residential electricity consumption per household is approximately 26% higher than an average household in the US (EIA, 2009). Texas has very hot summer seasons, which make the use of air conditioning substantial in the region. Aside from consumption, Texas is also different from these other areas studied because it does not have vertically integrated utilities to supply customers; instead it uses a fully competitive market model[4] with over 100 suppliers among which customers can choose. Also unique about this study is that it considers specifically how being low income and receiving state subsidies for electricity may impact a customer's ability to derive efficiency benefits.

1.2 DBES and MBES

First, it is important to note that Direct Energy's DBES is just one of many products available in the competitive market for customers to choose. DBES is available to all customers in Texas' competitive areas, including customers receiving energy financial assistance but excluding those on medical critical care qualification. The only other customer requirement is access to email or text messages to receive their bill and account updates. Direct Energy was an early mover in launching a DBES product, which it marketed in Texas under the name "Power-to-Go." Power-to-Go is now in the product suite of Direct Energy's First Choice Power brand.

Compared to MBES, DBES has fewer requirements of customers. For example, customers are required to pay a deposit or undergo a credit check to get a monthly billed service but not daily billed service. DBES customers also avoid fees MBES customers might face when they have trouble paying their bills. Table 1 summarizes some differences.

Table 1. Comparison of Features for MONTHLY and DAILY

Features	MONTHLY	DAILY
Requires a Credit Check	Yes	No
Requires a Deposit	Based on credit score	No
Monthly Invoice	Yes	No
Late Fee	Yes	No
Debt Collection Fees	Yes	No

[4] There are some pockets in Texas where the old utility structure remains that were carved out when the restructuring of the market was legislated. The most significant areas are San Antonio, Austin, and those areas inside Texas but outside of ERCOT. Direct Energy customers are only in the competitive areas of Texas.

To initiate service, a DBES customer deposits money into an account. Customers do not buy a defined number of kilowatt-hours at that time; the price of the kilowatt-hour is determined according to the day it is use, though both fixed- and variable-priced DBES products are available. The customer must maintain a positive account balance as calculated each business day. Transactions and updates are executed on a batch basis on business days, not in real time, though customer-initiated actions like payments are processed in real time. Direct Energy does not implement any activity during the weekend and is restricted by state law from taking any customer actions during severe weather events, such as extreme heat or extreme cold. Every business day, Direct Energy uses energy consumption data from the prior metered day to compute a bill and charge the customer's preloaded account (for example, on Wednesday morning, Direct Energy computes Monday's bill and debits that amount from the customer's account). Direct Energy communicates with the DBES customer at 8:00 a.m. each business day informing the customer of the daily total usage, the price per unit, the total daily bill, and the dollar amount remaining in the account. If the amount remaining in the account is below $0.00, Direct Energy informs the customer to add money by 10:00 a.m. or be disconnected. There are numerous vehicles to add cash to the customer's account, including web service, an inbound customer care center, and thousands of in-person payments centers at locations like grocery stores. Customers can make payments as often as they like and for any amount with no fees incurred. The average Direct Energy DBES customer makes over 5 payments per month (Direct Energy). If the customer fails to add money to the account by the deadline, Direct Energy uses the smart meter network in Texas to issue a remote disconnect through the local distribution utility.

There are no fees for late payment, debt collection, disconnections, or reconnections. A customer who is disconnected may add cash to his account at any time and Direct Energy is then obligated to restore his service through a remote reconnection process within 2 hours.

1.3 Lite-Up Texas

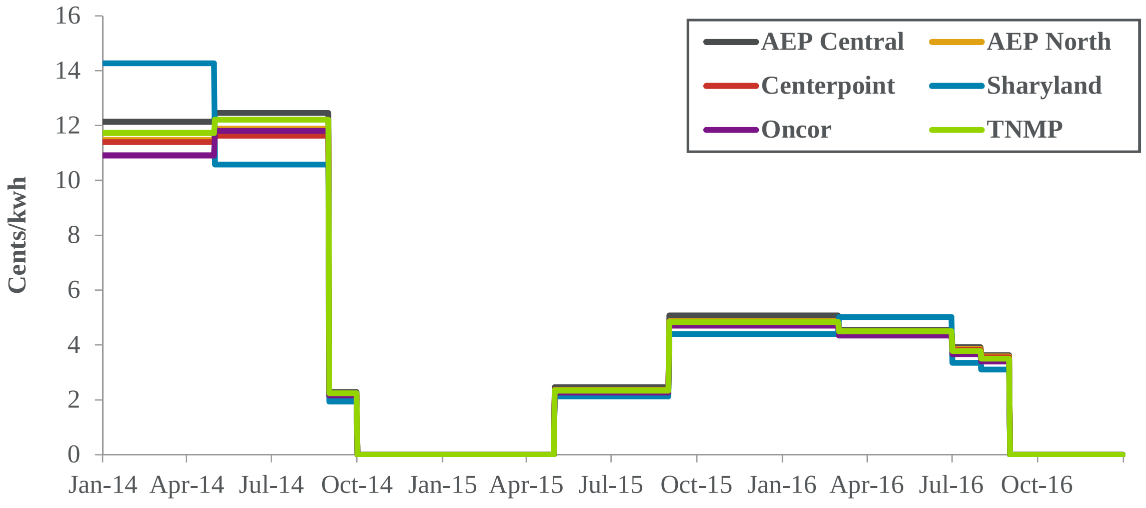
Lite-Up Texas is a subsidy program designed to provide assistance for low-income and energy-challenged Texans in paying their electricity bills. According to the provisions of the program, households in the Supplemental Nutrition Assistance Program (SNAP) or Medicaid qualified for

Lite-Up Texas.[5] An alternative application method involved proving that the household's total income did not exceed 150% of the poverty level, as defined by the US federal government. For example, a household with 5 people that has an annual income lower than $42,000 is considered as not exceeding 150% of poverty level.[6] Electric bills were reduced by the amount of the subsidy, which took the form of a subsidy per kilowatt-hour of usage. The subsidy appeared to customers as a line-item on their electricity bills.

One area of our research focused specifically on whether the efficiency benefits of the product are applicable to both low-income and non-low-income customers. Some critics have alleged that efficiency from prepayment is, in effect, 'forced savings' because those customers would be disconnected so promptly for nonpayment. We split our customer datasets between low-income and not low-income.

In 2013, the Texas legislature decided to discontinue Lite-Up Texas and to increase subsidies during our study window in order to deplete the fund. As a result, substantial subsidies were offered between 2014 and 2016, as shown in Figure 1 below. The fund was depleted by the end of 2016.

Figure 1. Lite-Up Texas Subsidies to Low-income Electricity Customers in Cents/kwh



[5] Public Utilities Commission of Texas https://www.puc.texas.gov/consumer/lowincome/Assistance.aspx
[6] Ibid.

Source: Public Utility Commission of Texas.

2. Customer Data

2.1 Four Customer Population Datasets

To study any energy efficiency benefit for DBES, we used Direct Energy's residential customer database with 15-minute interval data for the years 2014-2016. These customers were spread across the ERCOT competitive market territory. Depending on the sort of product chosen and whether or not they received Lite-Up subsidies, customers were assigned to four categories:

Table 2. Types of Residential Customers in Direct Energy

	MBES	DBES
Not Lite-Up	Conventional	Energy Managers
Lite-Up	Budget	Cash Managers

1) **"Conventional"** customers are the most common type of customer. They are not identified as Lite-Up (and therefore do not receive subsidies) and they use a traditional billing energy product, that is MBES.
2) **"Budget"** customers also use MBES, but they have been identified as Lite-Up and receive subsidies from the state.
3) **"Cash Managers"** are also Lite-Up and receive subsidies, but they have chosen a DBES product and can more actively manage their spending on electricity on a daily basis.
4) **"Energy Managers"** can actively manage their spending on electricity like "Cash Managers," but they are not subsidized in the Lite-Up program.

We used the entire populations of Budget, Cash Managers, and Energy Managers for the study. Each population had over 20,000 customer-years represented.[7] We selected a random sample of the Conventional customers, who are the most numerous. We employed power analysis to determine the appropriate sample size for the Conventional customer dataset to yield statistically meaningful results.[8]

2.2 Cleaning the data

Once the populations were determined, two key vulnerabilities were addressed. The first was the potential for a small subset of super-users to skew the averages because of the asymmetrical nature of the distributions of consumption. The second was the potential for a higher incidence of disconnections in one population group to cause us to mistake forced savings for behavioral change.

To address the first issue, we identified several extreme energy users and excluded these outlier customers from both DBES and MBES data, in addition to the customers who dropped out of the program in each year. An outlier customer is defined as a residential customer whose daily energy consumption is an order of magnitude greater than the median of the energy usage of the sample.

To address the second issue, we eliminated all zero-usage intervals when measuring the average usage for that interval by each population. But, by eliminating zero-usage intervals from the averages, we could count only the customers who were on-flow and be assured that any energy efficiency found would be independent of disconnections.

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[7] Due to the restrictions on releasing the competitive company data, we were not able to provide details on the average energy usage of the customers and load shapes. However, we encourage interested parties to contact the authors of this article.

[8] Power analysis is a method to determine the necessary sample size that would yield statistically meaningful results. In the context of this study, power analysis is a method to determine the necessary number for the control group of "Conventional" customers so that statistically significant energy savings could be calculated. The power of a sample is function of sample size, effect size (i.e., percent savings) and the level of statistical significance. NERA assumed the effect size as 11% based on the findings of the previous studies. NERA also assumed that the sample control group customers (i.e., "Conventional") are equal to the treatment group ("Energy Managers"). Finally, we assumed a 99% statistical significance level. Feeding these assumptions into the power analysis, we estimated the standard error on the assumed percent savings using linear regression. Then, we evaluated the level of statistical significance in assumed savings at various numbers of Conventional customers (e.g., 10,000, 20,000, 30,000; and so on). We determined that 40,000 customers would yield statistically significant results at 99% confidence level.

3. Empirical Methodology

3.1 Self-selection bias

Self-selection bias arises when customer choice for a given product is not truly random (Heckman and Robb, 1985). Because Direct Energy operates in a competitive marketplace, product choice is not random and not controlled (i.e., self-selection bias is unavoidable in a non-experimental setting where the phenomenon being studied reflects individual choices that may be driven by unobserved factors.). Indeed, because of the features of the DBES product, one can expect it to appeal particularly to consumers who are credit-challenged, who have cash management concerns, or who are proactive in energy efficiency.

There are methods to address self-selection bias in empirical analysis. Two commonly used methods are the "matching method" and "instrumental variable" approach.[9] We used the instrumental variable approach, which assumes a strong correlation between an intermediate variable and the variable of interest (i.e., decision to participate). The instrumental variable approach is preferred mainly because, unlike the matching method which would require us to impossibly justify and measure all determinative household characteristics, we are able to validate the instrumental variable with statistical methods. An acceptable instrumental variable is highly correlated with DBES and not correlated with the customer's energy consumption.

For this study, we assume the DBES adoption rate is highly determinative of decision for becoming a DBES customer. Specifically, we defined customer adoption rate "$Adoption_i$" as the percentage of a given zip code's Direct Energy customers that have selected a DBES product. Adoption rate is highly correlated with the customer product preference (i.e., DBES or MBES) and not directly related to customers' energy consumption (Sun 2018 and Miller 2006).[10] We employed a two-stage least squares (2SLS) estimation methodology.[11]

3.2 Regression analysis on product impact

In the first stage of the two-stage least squares estimation, we used Adoption rate to predict customer's product choice, which is the variable called "$Treatment_{i,t}$". This variable takes the value 1 for the DBES customers and 0 otherwise.

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[9] The matching method assumes a selection process based on all observed household characteristics; however, this is a strong assumption because it is near impossible to comprehensively capture all the factors influencing the household decision.

[10] This instrumental variable is also used in Sun (2018) and Miler (2006) studies in evaluating energy efficiency and a health policy.

[11] We used Stata software to estimate the 2SLS regression equation. Standard errors are corrected for the system.

Using the predicted $Treatment_{i,t}$ from the first stage, we estimated average energy savings for Energy Managers and Cash Managers separately in the second stage of Regression Equation 1. The estimated coefficient b_1 on the $Treatment_{i,t}$ variable represents the average daily energy savings per customer.[12] We also control for humidity and time-fixed effects[13] in the second stage of Regression Equation 1.

Equation 1. Empirical Model Specification for Energy Impacts

First Stage:

$$Treatment_{i,t} = a_o + a_1 Adoption_i + a_2 Humid_t + \varphi_t + \tau_{i,t}$$

Second Stage:

$$kWh_{i,t} = b_o + b_1 Treatment_{i,t} + b_2 Humid_{i,t} + \varphi_t + \varepsilon_{i,t}$$

Where i=customer; t=day

$kWh_{i,t}$= Average daily usage of customer i on day d

b_o= Customer specific fixed effect (i.e., controlling for the customer characteristics that do not change over time such as house size)

b_1=Average daily energy savings for DBES customers (i.e., Energy Manager or Cash Manager)

b_2=The coefficient that captures the impact of average daily dew-point by customer zip code on average daily energy consumption

$Adoption_i$= DBES product adoption rate by zip code (i.e., percentage). This variable is used as the instrumental variable to correct for self-selection bias.

$Treatment_{i,t}$=An indicator variable taking the value 1 if the customer is a DBES customer or 0 otherwise.

$Humid_{i,t}$= Average daily dew point by customer zip code that captures the humidity.

[12] We have validated our instrumental variable approach using statistical tests however, exclusion restrictions (i.e., instrumental variable influences the outcome variable only though the endogenous variable) are not testable.
[13] There are more than 900 zip codes in the customer data. We tested whether the average daily usage is statistically different within a zip code.

φ_t= Time fixed effects. This is a set of indicator variables that controls unobserved factors that change over time such as daily, monthly and seasonal impacts on average daily energy consumption.

$\varepsilon_{i,t}$= Identically and dependently distributed error term of the regression model.

It is important to note one limitation of this study is that we were not able include energy usage data for customers prior to becoming a DBES customer due to data limitations.[14]

3.3 Subsidy impact

We also attempted to examine the impact of the Lite-Up subsidy by comparing the energy consumption of Cash Managers to Energy Managers and of Budget customers to Conventional customers. Cash Managers and Budget customers receive subsidies, and Energy Managers and Conventional customers do not.

However, there were inputs we could not account for such as household income. While Lite-Up status provided a useful indicator of household income when analyzing for the impact of product on energy consumption, it becomes confounding when the analysis tries to slice the data the other way. The effect we could find in that analysis is not truly a subsidy effect, but an income-and-subsidy effect. Without reliable household income data – which Direct Energy did not collect on these customers – any such analysis would be inconclusive; therefore, we leave this part of the analysis to future research.

4. Findings

4.1 Overall efficiency of 9.60%

The first and most important finding was that there is a statistically significant energy efficiency resulting from the DBES product for both DBES populations though Cash Managers enjoyed less energy efficiency than Energy Managers did. The weighted average (including both Lite-Up and non-Lite-Up populations) efficiency is 9.60%.These savings are not impacted by any disconnections because intervals with zero usage were excluded from the calculation.

[14] In other words, this study only quantifies the energy savings from Direct Energy's DBES product in relation to MBES customers but does not compare to DBES customers' energy consumption prior to participating in the DBES. Our estimated energy savings for this DBES product is subject to change if we were able to condition the energy savings estimate based on customers' energy consumption prior becoming a DBES customer as well.

Energy Managers saved approximately 10.74% of their average energy consumption between 2014 and 2016 compared to Conventional customers. The energy savings of Energy Managers are shown by year in Table 3.

Table 3. Estimated Energy Impacts for Energy Managers

Year	Estimated Savings kWh/day/customer	Robust Standard Error	Percent Savings
2014	3.71	0.02	9.58%
2015	3.73	0.02	9.44%
2016	5.07	0.01	13.21%

Note: We calculated the robust standard errors and calculated the confidence intervals with robust standard errors.

We see a more muted 3.52% energy efficiency for Cash Managers compared to Budget customers for the average of years between 2014 and 2016. While these customers received subsidies that could encourage more consumption, both Cash Managers and Budget customers received the same level of subsidy. More study is needed to understand why less efficiency is available to this subpopulation. See Table 4 for energy efficiency savings by year for Cash Managers.

Table 4. Estimated Energy Impacts for Cash Managers

Year	Estimated Savings kWh/day/customer	Robust Standard Error	Percent Savings
2014	0.32	0.04	0.92%
2015	1.04	0.03	2.87%
2016	2.50	0.02	6.79%

Note: We calculated the robust standard errors and calculated the confidence intervals with robust standard errors.

5. Discussion and Conclusions

5.1 Summary conclusions

This study follows in the footsteps of several similar studies in the past that have sought to quantify the energy efficiency behaviors that prepaid energy products engender, and the efficiency findings fall in line with the findings of these other studies. Unlike other studies that have tested regulated utility program, this study shows the benefits are maintained in a competitive market. Seen through these lenses, DBES products could present a compelling case to be a transformational product in the energy marketplace.

5.2 Efficiency benefit of DBES confirmed

The most essential finding of this study is that DBES does have an energy efficiency benefit of approximately 9.60%[15], with an average 10.74% for non-Lite-Up households, which constitutes the great majority of households. This benefit is net of any reduction in consumption from disconnections. Energy efficiency stems from more engagement by the customer with his energy service. The DBES customer has more frequent communications about his usage and the associated cost, more granular information, and more real-time information. But, beyond that, DBES not only provides deeper information; it enables a customer to relate his costs to his benefits in a timely and concrete financial transaction that makes the communication 'more real.'

The observable efficiency benefit of DBES was not as great for the Lite-Up data set. Further study into the reason for the difference in efficiency would be worthwhile. There are a few hypotheses here worth exploring:

(i) the significant subsidies received by the Lite-Up populations, though they were equal, may nevertheless have blunted any incentive to be mindful of efficiency;
(ii) because these populations are low-income, they may already be more mindful of energy cost burdens without the engagement provided by DBES;
(iii) as low income populations, they may be likelier to live in apartments, where heating and cooling are a lower share of their overall demand, making simple measures like changing the thermostat setting less impactful.

Whatever the reason for the lower benefit, the Lite-Up populations still achieve a worthwhile efficiency gain.

5.3 Implications of findings

The financial impact of this efficiency can be quite significant. An Energy Manager using approximately 14 MWh per year and paying 12 cents per kWh would save $183 per year from

[15] We weighted percent energy efficiency savings including Lite-up and non-Lite-up customers using the customer populations.in each customer group.

this efficiency. By way of example, if all residential customers in Texas switched to DBES, savings would top $800 million per year if all residential realized a 9.6% efficiency benefit.[16] Besides the energy savings, the efficiency could lower peak capacity requirements, meaning fewer expensive peaker-plant generators would need to be maintained in the generation stack, which is also an area of future research.

Table 7. Bill Savings for DBES Energy Managers and Cash Managers

Customer Type	MBES Average Usage (kWh/Year)	Efficiency Benefit (%)	Efficiency Benefit (kWh/Year)	DBES Avg. Usage (kWh/Year)	Avg. Bill Rate ($/kWh, assumed)	Money Saved ($/Year)
Average DBES	13,870	9.60%	1,332	12,539	$0.12	$160
Energy Managers	14,211	10.74%	1,526	12,684	$0.12	$183
Cash Managers	13,049	3.52%	460	12,589	$0.12	$55
Customer Pays					$0.07	$31
Lite-Up Subsidy					$0.05	$25

Note: (1) The assumption on the average bill rate is for illustration purposes. Direct Energy has several other bill-rate offering products. (2) Cash Manager's bill rate is lower due to the annual subsidy.

Beyond the energy and monetary savings, a DBES approach can change the way people interact with their energy and manage their households. This engagement with energy consumption can yield new dynamics as we move into a distributed generation economy in which consumers of energy can also be producers of energy. The outmoded monthly billing arrangement will not continue to be sufficient in a new energy economy, which we will continue to explore in our future research.

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