

# Equity in Residential Electricity Pricing

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*Real-time pricing of electricity is theoretically more economically efficient than flat rate pricing. However, a switch from flat-rates to real-time rates means that many consumers will lose the cross-subsidy they are receiving under the flat rate, and may see an increase in their bills even if they have elastic demand. We use hourly load data from 1260 Commonwealth Edison residential customers on a standard flat rate electricity tariff from 2007 and 2008. We calculate which customers would have been better off and which customers would not under real time pricing with both elastic and inelastic demand and look at the general characteristics of these customers. We find that if customers do not respond to prices under RTP, then only 35% of customers save money, while the remainder loses. The greatest potential for savings is from reduction in capacity costs.*

**Keywords:** Residential electricity pricing, dynamic pricing, real-time pricing

## 1. INTRODUCTION

Wholesale and retail electricity prices are decoupled for most residential electricity customers. Wholesale prices change in real time to reflect marginal cost and can range from negative values to \$1000/MWh<sup>1</sup> (PJM Interconnection, 2009). Residential retail rates are typically flat rates, which are load weighted averages of expected price over a certain period of time<sup>2</sup> (typically a year or more). Flat rate (FR) pricing is inefficient because price does not reflect marginal cost, so customers may be under- or over-consuming at any point in time (Borenstein and Holland, 2005; Spees and Lave, 2008). Customers

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<sup>1</sup> In the PJM Interconnection, a regional transmission organization serving 13 US states.

<sup>2</sup> Some utilities offer residential customers alternative tariffs including: time-of-use pricing, critical-peak pricing, real-time pricing, inclined block pricing.

with a high coincident peak relative to their average demand are, on average, paying below marginal cost<sup>3</sup> while customers with flatter usage or those whose peak demand occurs at off-peak prices are paying above the marginal cost they impose, on average (Spees and Lave 2008). Customers that add to peak load impose high costs on the system, but under FR pricing, all customers pay the same amount. This is a policy where customers with high coincident peaks are receiving a cross-subsidy from the remaining customers.

Real-time pricing (RTP) has the potential to address these problems by directly coupling retail and wholesale prices. The energy charge in a residential RTP tariff changes hourly to reflect either the day-ahead or real-time locational marginal energy price (LMP). This provides a signal for customers to use only the amount of power that they value at or above the current marginal price of power. If customers respond to high prices by lowering usage, RTP can potentially lead to lower peak demand and price. Even if only some customers respond, all customers can potentially benefit from lower marginal price and lower capacity costs due to lower peak demand. Charging customers the RTP is no guarantee that customers will reduce or shift load when price is high. The potential savings must be large enough for customers to invest in the time, education and technology necessary to effectively reduce peak demand. Several utilities including Commonwealth Edison (ComEd) and Ameren currently offer optional RTP tariffs to residential customers. Other utilities offer approximations of RTP such as time-of-use (TOU), where days are divided into peak and off-peak prices for electricity or critical-peak pricing (CPP) where higher prices are triggered by high wholesale prices or a correlated metric such as temperature.

Borenstein and Holland (2005) show that increasing the share of customers on real-time pricing is likely to improve efficiency. Borenstein (2005) shows that even with small elasticities, gains in economic efficiency from RTP can be substantial. We will not elaborate any further on the inefficiencies of flat rate pricing and the potential efficiency gains from dynamic pricing, since there is already substantial literature on this subject (see: Borenstein et. al., 2002; Borenstein and Holland, 2005; Holland and

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<sup>3</sup>The total price of electricity is set to average cost, not marginal cost. Average cost can be greater than marginal cost (high fixed costs) or lower (in systems where there is a limited quantity of cheap power). We refer here only to the portion of the price that is for energy.

Mansur, 2006; Spees and Lave, 2007; Borenstein, 2005). Instead we will focus on the distributional impacts of dynamic pricing.

Here, we address a question of practical importance to electric utilities and public utility commissions who are considering a move to dynamic pricing: which consumers “win” (will save money under RTP compared to FR) and which consumers “lose” (lose money under RTP compared to FR) when switching from FR to RTP? Because of the inherent cross-subsidies between customers under FR pricing, when a utility switches to dynamic pricing, the cross subsidy will be reduced (CPP) or disappear entirely (RTP), and the cost burden will shift from customers with flatter loads or non-coincident peaks to those with high coincident peaks. Some customers may experience significant changes in their bills – both increases and decreases if they don’t shift their usage. It will be important for utilities and PUC’s to know in advance which customers will have large bill increases, so they can supply those customers with information and tools to help mitigate the increased bill by increasing energy efficiency or shifting or curtailing load, or create policies to tax the “winners” and subsidize the “losers”.

The question can be reframed for those utilities that are not considering a switch to RTP: which customers are currently providing cross-subsidies to other customers under FR pricing? Is the wealth transfer caused by the cross-subsidies an acceptable policy from an equity perspective?

We address these questions by taking a sample of customers and calculating their bill difference under RTP and FR under both inelastic and elastic demand. We treat the scenario with inelastic demand as a zero-sum game used to explore cross-subsidies: one customer’s loss is another’s gain. This is also a “worst case scenario” for RTP programs, where consumers don’t respond, so there are no net savings to consumers. Under elastic demand, there are net savings to consumers due to avoided energy usage, lower marginal prices and lower capacity costs. We then analyze customer characteristics including income and demand. We obtained data from a sample of ComEd customers.

Borenstein (2012) and Faruqui et. al. (2010) also perform empirical analyses of the distributional effects of dynamic pricing. Our analysis differs in several ways: we use an RTP tariff while the other

analyses focus on variations of TOU and CPP; we focus on different geographic regions which have different load and price characteristics; our analysis assumes a mandatory tariff, while the other analyses assume opt-in tariffs.

We find that under inelastic demand, only 36% of consumers would save money under RTP. With elastic demand of -0.2 (an upper bound), roughly 50% of customers would save money from reductions in energy usage and energy price. Many more customers save if we assume reductions in capacity costs due to demand response. The customers who save tend to be the largest consumers, while those who would lose money under RTP tend to be smaller consumers and represent a disproportionate amount of low-income customers.

The remainder of this paper is organized as follows. Section 2 describes the data set. Section 3 explains the analysis for inelastic demand and 4 models elastic demand. Section 5 gives the policy implications of the analysis.

## **2. DATA SET**

### **2.1 Usage**

ComEd serves Northern Illinois and the greater Chicago area and is part of the Regional Transmission Organization PJM Interconnection. ComEd has an optional residential RTP tariff currently in use, so we were able to use actual tariffs (adjusted to be revenue neutral, see appendix B) in our calculations. We have hourly electricity data from a stratified sample of 1260 residential customers from 2007 and 2008. Some of the strata were oversampled, however corrections were made for this in all statistics using the bootstrap method (Appendix C). While simple weighting is adequate to get point estimates for the mean, etc. bootstrapping is necessary to obtain a distribution with confidence intervals.

These customers were all on a residential FR tariff, so there are no confounding behavioral factors due to exposure to RTP. We know which of four customer classes each customer belonged to: (1) single family (SF); (2) multi-family (MF); (3) single family with electric space-heat (SFH); and (4) multi-family with electric space heat (MFH) (see table 1 for summary statistics). We also have data on whether

customers received any need-based subsidies (table 1). There are several income-based subsidies customers can qualify for<sup>4</sup>. We classified any customer that received any need-based subsidy at any point over 2007 or 2008 as “low income”. Approximately 6% of customers in the population are low income by this definition.

Table 1: Summary statistics by customer class in ComEd population and sample for 2007-2008.

Customer Class	Total accounts	Percent (population)	Accounts in sample	Subsidized in sample	Average usage (kWh/h)
Single family (SF)	2,200,000	64.8	344	13	1.3
Multi-family (MF)	1,000,000	29.7	264	17	0.5
Single family space-heat (SFH)	35,000	1.0	169	6	3.9
Multi-family space-heat (MFH)	155,000	4.5	482	89	1.4
Total	3,400,000	100	1259	125	1.1

The raw data, consisting of hourly household electricity usage were cleaned and verified so that all remaining data were valid. The protocol used for cleaning the data is in Appendix D.

## 2.2 Tariffs

ComEd residential electricity bills are monthly bills and consist of three sections: (1) electricity supply services, (2) delivery services, and (3) taxes and other. There are several different charges in each section. Some charges are the same for both RTP and FR customers; some charges are different and in some cases a charge is exclusive to either RTP or FR. Charges can be either fixed monthly costs or based on the amount of electricity consumed that month (i.e. a cost per kWh). The one exception is the capacity charge, which is applied only to RTP bills. Customers are billed per kW-month of demand, where demand is the customer’s average usage during the 10 hours of highest system usage. Appendix A gives details on the rates and how bills are calculated. Table 2 shows the average annual bill for each customer class.

<sup>4</sup> The subsidies are: Low Income Home Energy Assistance Program (LIHEAP) Payment, ComEd Space Heat Credit, Summer Bill Credit, Rate Relief Credit, Residential Special Hardship and Chicago Housing Authority (CHA-CARE) All Clear Credit

Table 2: Average annual bill over 2007-2008 in a revenue neutral scenario.

Customer Class	Percent (population)	Average annual bill (\$/yr)
Single family	64.8	1290
Multi-family	29.7	560
Single family space heat	1.0	2530
Multi-family space heat	4.5	970
Total	100	1070

For customers that are on RTP, the only portion of the bill that changes hourly is the energy supply charge, which corresponds to the wholesale LMP. Over 2007 and 2008 the RTP energy supply charge ranged from  $-25\text{¢/kWh}$  to  $50\text{¢/kWh}$  with a mean value of  $5\text{¢/kWh}$ , a median of  $4\text{¢/kWh}$  and a standard deviation of  $3\text{¢/kWh}$ . 90% of prices were between  $1\text{¢/kWh}$  and  $10\text{¢/kWh}$ , while 50% of prices were between  $3\text{¢/kWh}$  and  $7\text{¢/kWh}$ . Prices exceeded  $15\text{¢/kWh}$  1% of the time. The RTP energy supply charge represents 45% of the total average annual electricity bill<sup>5</sup>.

The flat rate energy supply charge ranged from  $4.4\text{¢/kWh}$  to  $7.6\text{¢/kWh}$  depending on the month and customer class<sup>6</sup>. All other rates (both marginal and fixed), for both FR and RTP are constant throughout each billing cycle, but may be adjusted, no more frequently than monthly, to reflect changes in cost.

### 3. ANALYSIS: NO BEHAVIOR CHANGE

In this section we calculate the difference in annual electricity bill for the sample, had the customers been on RTP, compared to what they actually paid under FR. It should be noted that all of the customers in the sample were on the FR, and were at no point on RTP during this time period. We apply

<sup>5</sup> This calculation, as well as all other calculations in this paper does not include taxes, so in reality the supply charge represents a smaller portion of the total bill.

<sup>6</sup> It should be noted that the energy supply charge for FR customer includes the capacity payment, but is a separate charge for RTP customers, so the energy supply charge under FR and RTP are not comparable.

the RTP tariff that was optional for ComEd customers at that time to the electricity usage of the customers in the sample.

We calculate the difference in annual electricity bills for the sample of customers, had they been on RTP without any behavior change. The goal of RTP is to give consumers a price signal so that they can modify their behavior, however there is no guarantee of behavior change. Price differentials must be large enough for customers to save money, the prices must be communicated effectively, and consumers must have the resources to react. We first compare bills with the assumption of no behavior change for several reasons: (1) it provides a worst case scenario for bill changes (2) it gives us information on residential cross subsidies under flat-rates (3) it informs us which customers need the most help from utilities in controlling bills and technology for behavior change under switches to dynamic pricing.

### **3.1 Assumptions**

In order for the results to be applicable to other utilities, we proceeded as follows. All subsidies are removed from the analysis so it can be generalized to areas that do not have these subsidies. ComEd space heating customers receive a significant subsidy on their energy supply charge (ranging from 2.4 – 2.8¢/kWh depending on season and customer class, or roughly 1/3 of the energy supply charge). This subsidy was removed from the analysis. The first 100,000 RTP customers in ComEd receive a \$5 subsidy on their smart meter lease. This subsidy is not included in the analysis, so the analysis can be applicable to rollouts where there will be no meter subsidy. Low income subsidies were not included when calculating bill differences, since it is presumed that the same subsidy would be applied under FR or RTP, and the FR and RTP bills are differenced.

The charges in the electricity supply services portion of the bill are pass-throughs, and go directly to PJM or the generators to cover the associated costs. In theory, if customers consume the same amount of energy at the same times, the total energy supply costs should be the same under RTP or FR. However, this does not occur because at present ComEd procures power for FR customers via a combination of long term contracts and spot market purchases, while all of the RTP energy is purchased

directly on the spot market. Due to hedging premiums and the lack of perfect foresight for future spot market prices, the cost of power under long term contracts is not the same as the equivalent power bought on the spot market. If there were to be a larger shift towards RTP however, buying all RTP power on the spot market as is currently done would not be feasible. In order to provide generators and the market with the certainty they need (to acquire capital at reasonable rates) long term contracts are necessary (Hirsh, 1999). To account for this, we have adjusted the FR bills to be revenue neutral with RTP, so that the total revenue under either rate is the same, it is just distributed differently amongst customers. See appendix B for details on revenue neutral calculations.

Even with these assumptions, these results may not be generalizable to other utilities and regions. Generation profiles (i.e. availability of coal, oil, etc.), demand profiles, customer makeup (i.e. industrial, commercial, residential), transmission constraints and weather are just some of the factors specific to each utility and region that can change these results. The data we have comes from a summer-peaking utility. Result would be significantly different in a winter peaking area. Nevertheless, the lessons learned here can inform policy makers in other areas and justify the need for further study.

### **3.2 Results**

Figure 1 shows the distribution of percent bill changes for ComEd customers had they been on RTP compared to FR with inelastic demand and a 95% confidence interval (CI). Negative percent changes indicate a savings on RTP relative to FR. Roughly 36% (95% CI: [34% - 39%]) of customers would have done better under RTP compared to FR, while the remaining 64% of residential customers would have lost money had they been on the RTP tariff without shifting or curtailing any of their usage in response to fluctuating prices. Under RTP, the bills of approximately 70% of customers fall within 10% of their FR bills. 10% of customers will see a significant increase: 20% or more in their annual electric bills. About 1% will see an increase greater than 30%. The median customer would lose \$25 [\$23-\$27] per year if she switched to RTP. As a check that we properly performed the revenue neutral adjustment,



the mean change in bill is statistically indistinguishable from zero (mean change of  $-\$0.37/\text{yr}$  [ $-\$5.10/\text{yr}$ ,  $\$3.80/\text{yr}$ ]).

Another way of framing this is that under the current FR pricing, 36% of residential customers are providing a cross-subsidy to the remaining residential customers. This is because the 36% of customers use more power when power is below average price, while the remaining customers use more power when power is above average price. We will explore the reasons behind this result in the remainder of this section.

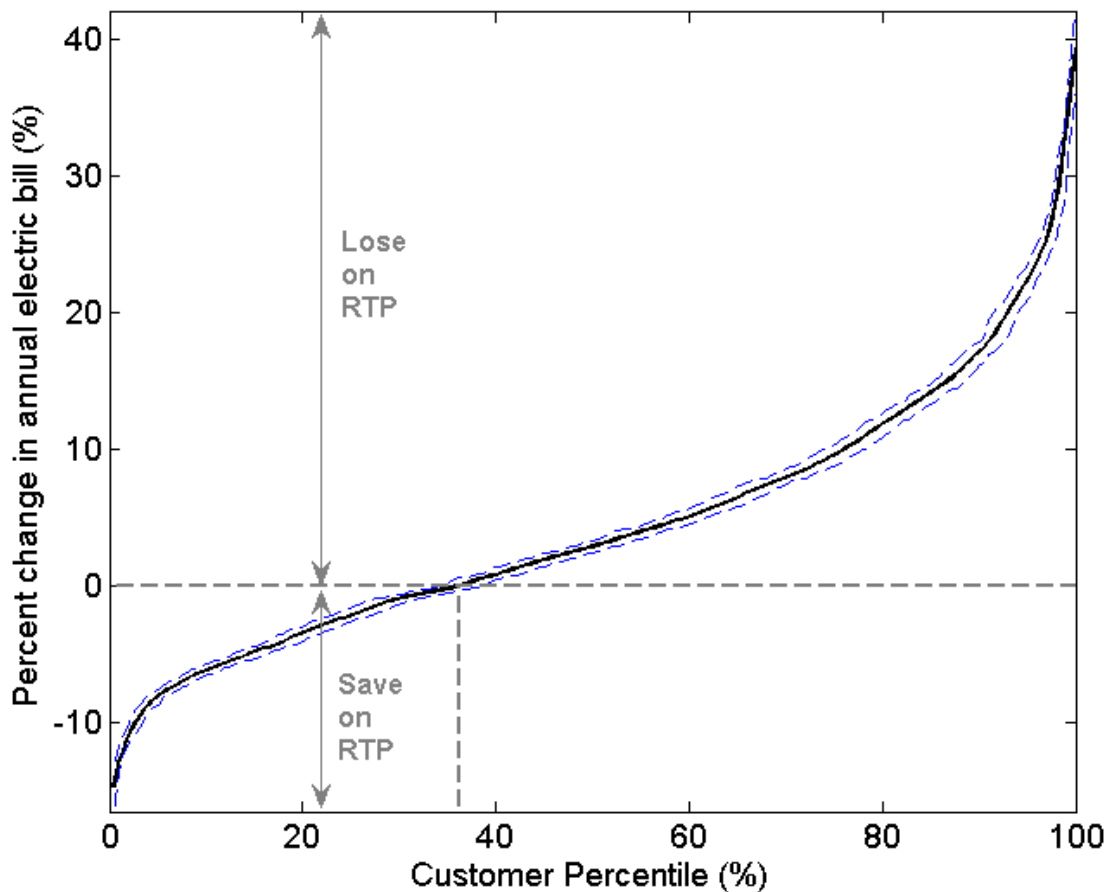


Figure 1: Distribution of annual bill changes, as a percent change from flat rate bills for all customers with 95% confidence interval.

The distribution in figure 1 is asymmetric. Despite the fact that the analysis was done so that the switch to RTP would be revenue neutral (i.e. gross revenue from residential customers is the same under RTP and FR), all of the savings go to just 35% of the customers. Another asymmetry is that the maximum savings is 20% while the maximum loss is more than double, exceeding 40%. When the distribution is plotted against the absolute bill change instead of the percentage of bill change, as in figure 2, the distribution, of course, still crosses zero at the same place, but the asymmetry with respect to the vertical axis is now switched and more exaggerated – in absolute terms the maximum savings (\$1000) is an order of magnitude larger than the maximum loss (\$150). Only 36% of customers would save in a zero-sum tariff switch, but these customers save more money, even though they save a smaller fraction of their bills. The 64% of customers who lose money under RTP lose a smaller magnitude of money, but that represents a higher fraction of their annual bills.

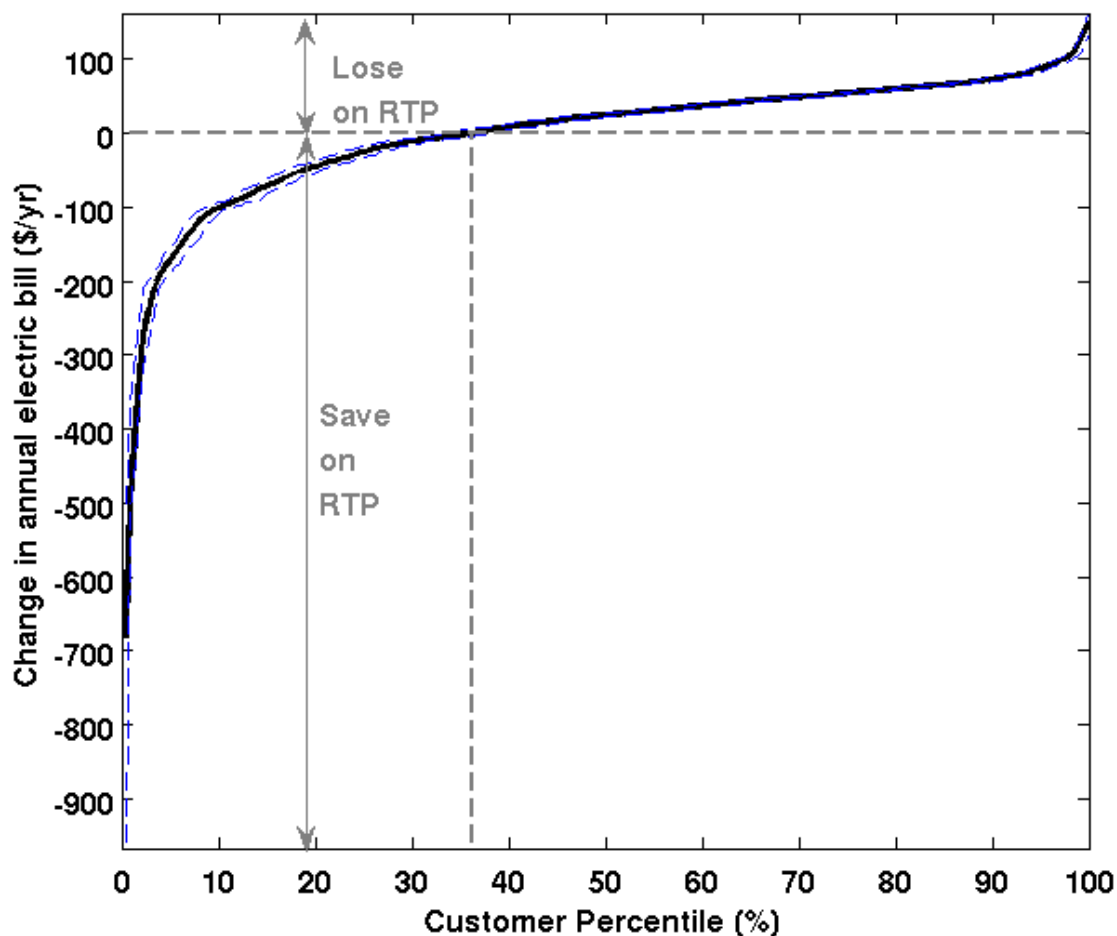


Figure 2: Distribution of annual bill changes for all ComEd customers in \$/yr with 95% confidence interval.

Figure 3 shows change in bill as a function of average hourly household energy consumption and shows that the relationship is roughly inversely proportional. There is a positive correlation between customers with high consumption and those who would have saved more under RTP, while those who consume less electricity tend to lose under RTP. Under the current FR, the largest users are providing a cross-subsidy to smaller customers.

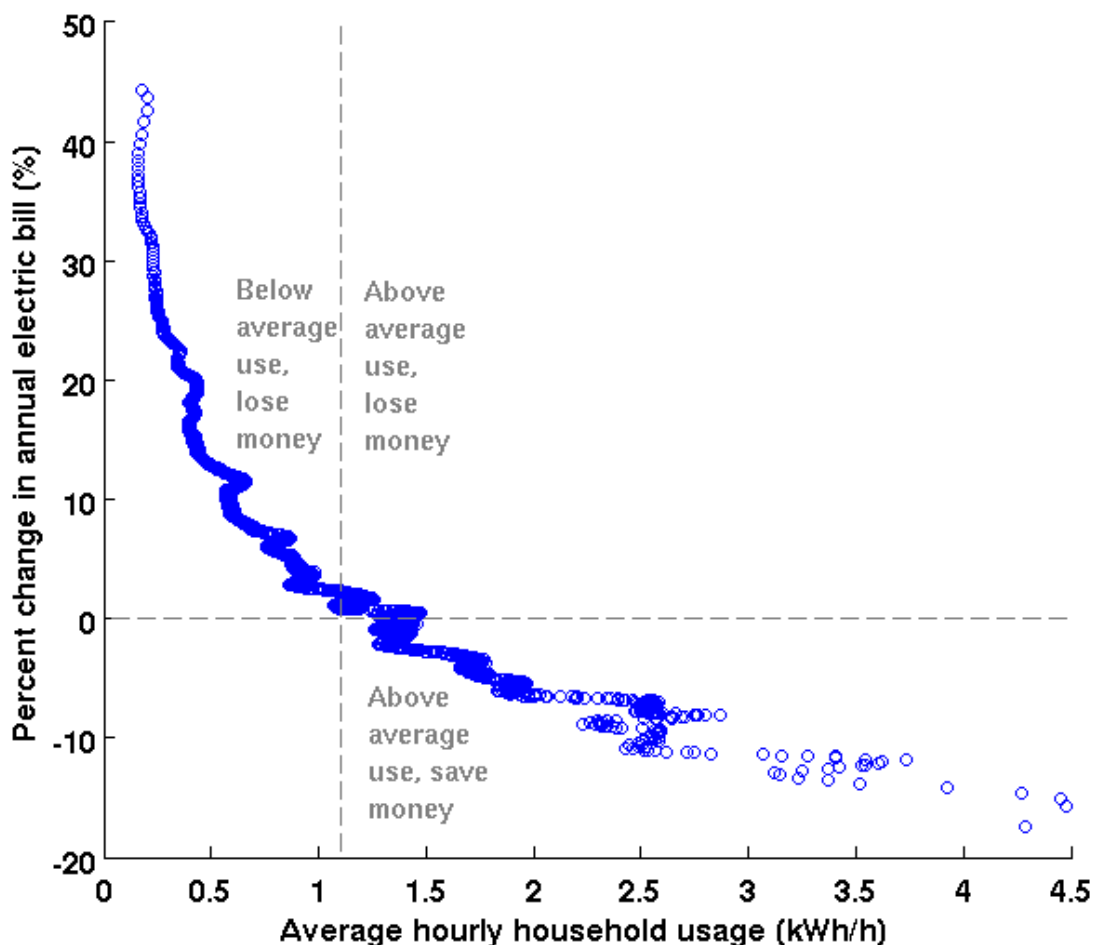


Figure 3: Average hourly household electricity consumption vs. absolute annual difference in bills. Points shown are averages from a bootstrap, in order to be representative of the population.

In order to understand why large customers consistently save under RTP and small customers consistently lose, we analyze how each segment's usage coincides with price. Price has both a daily and seasonal cycle. The daily price profiles for summer, winter and overall 2007-2008 are in figure 4. In ComEd's region, the seasonal cycle is that price peaks in the summer and is lowest in fall and spring. In the summertime, daily price follows temperature, peaking at around 4 p.m. and reaching a low near 3 a.m. In the winter, price dips during the hottest part of the day.

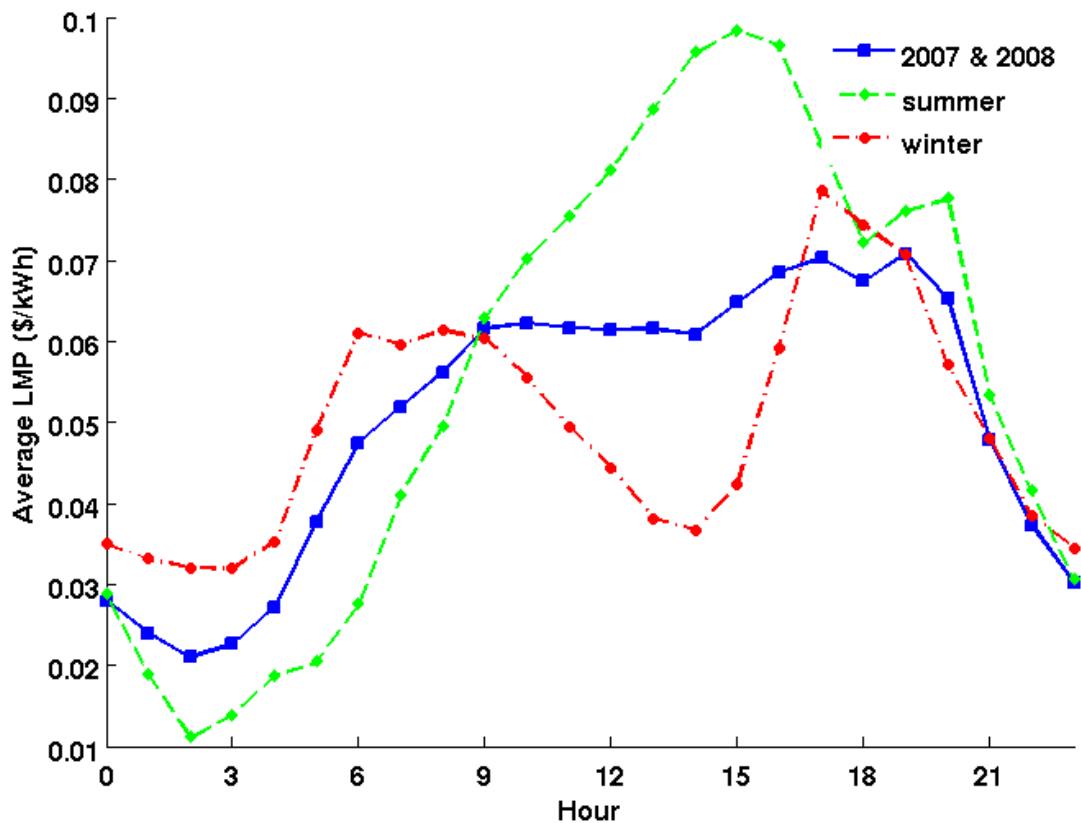


Figure 4: Daily locational marginal price (LMP) profile for ComEd for 2007-2008.

We now look at the usage patterns of the 5% of customer who save the most under RTP and the 5% of customers who lose the most under RTP, and examine how the interactions between price and usage determine the winners and loser. Figure 5 shows the load profiles for the top and bottom 5% of customers for the summer, winter and the entire year. The customers who win under RTP use a lot of power, however they using a lot of power all the time – summer, winter, day, night. They have a higher base-load (the minimum amount of power they use). Those who lose under RTP are using very little power, however when they do use power, it is during times of high price – during the summer, during the afternoon. They have low base-load and high peaks. The ratios for average peak to base usage for the

top 5% winners and losers is in table 3. The reason larger customers save under RTP is because they are using a lot of power when power is cheap – not because they use little when it is expensive.

Table 3: Ratio of average daily peak to base usage for the top 5% biggest winners and losers under RTP.

	Winners	Losers
Entire year	1.4	1.8
Winter	1.2	1.8
Summer	1.5	2.2

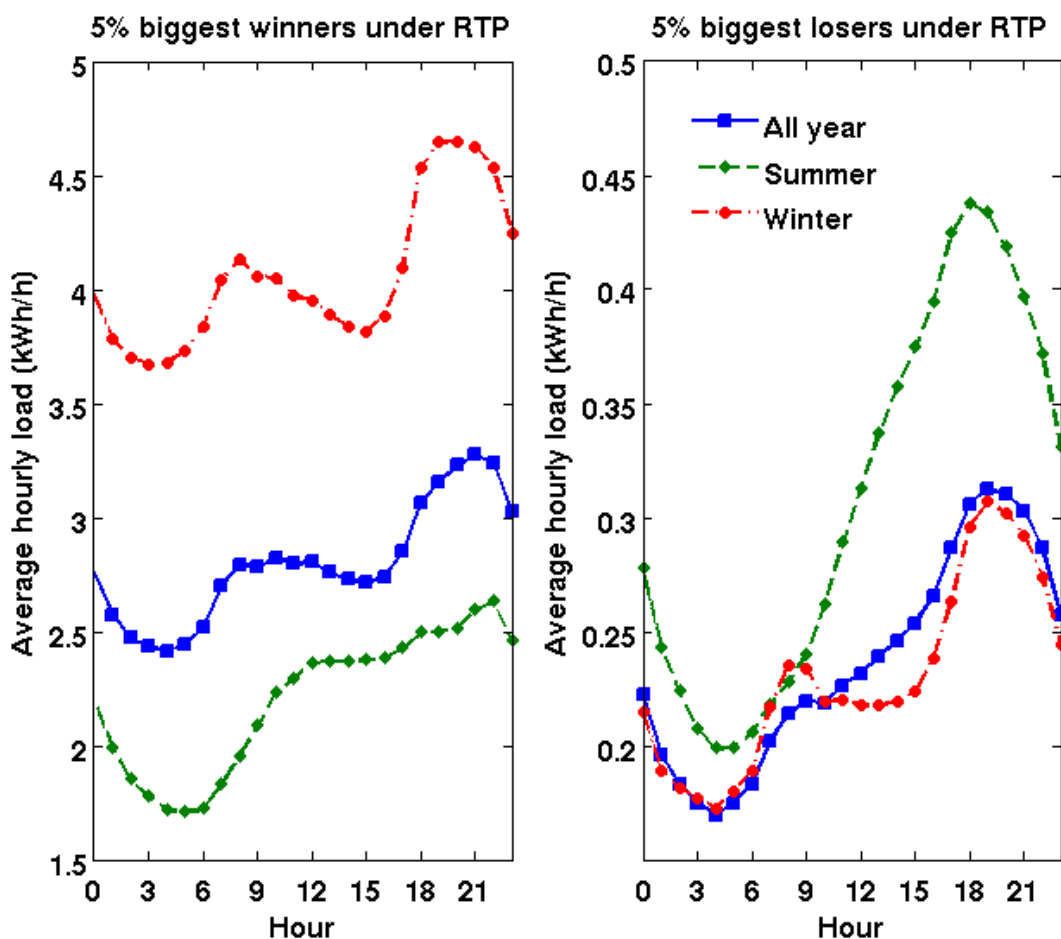


Figure 5: Average load for the 5% of customers who save the most under RTP (left) and 5% of customers who lose the most under RTP (right).

It should be noted that the load profile for the winners is dominated by electric space heating customers, which is why the load profiles are winter peaking. If these customers are removed, the load profile for the winners switches to summer peaking, however the implications remain the same: the ratios

of summer to winter usage and peak summer usage to base summer usage is lower for winners than losers despite the fact that the average usage of winners is much higher than losers.

### 3.3 Low Income Customers

Figure 6 shows the distribution of bill change for low income customers and the remaining customers. 19% of low income customers would save under RTP, while 37% of non-low income customers would save. This is not because low-income customers use power differently from similarly sized regular customers – in fact, their usages are, on average, statistically indistinguishable at the 95% confidence level. The lower rate of savings under RTP for low-income customers is an artifact of low-income customers having lower than average usage for their customer class, and smaller users tending to lose money on RTP.

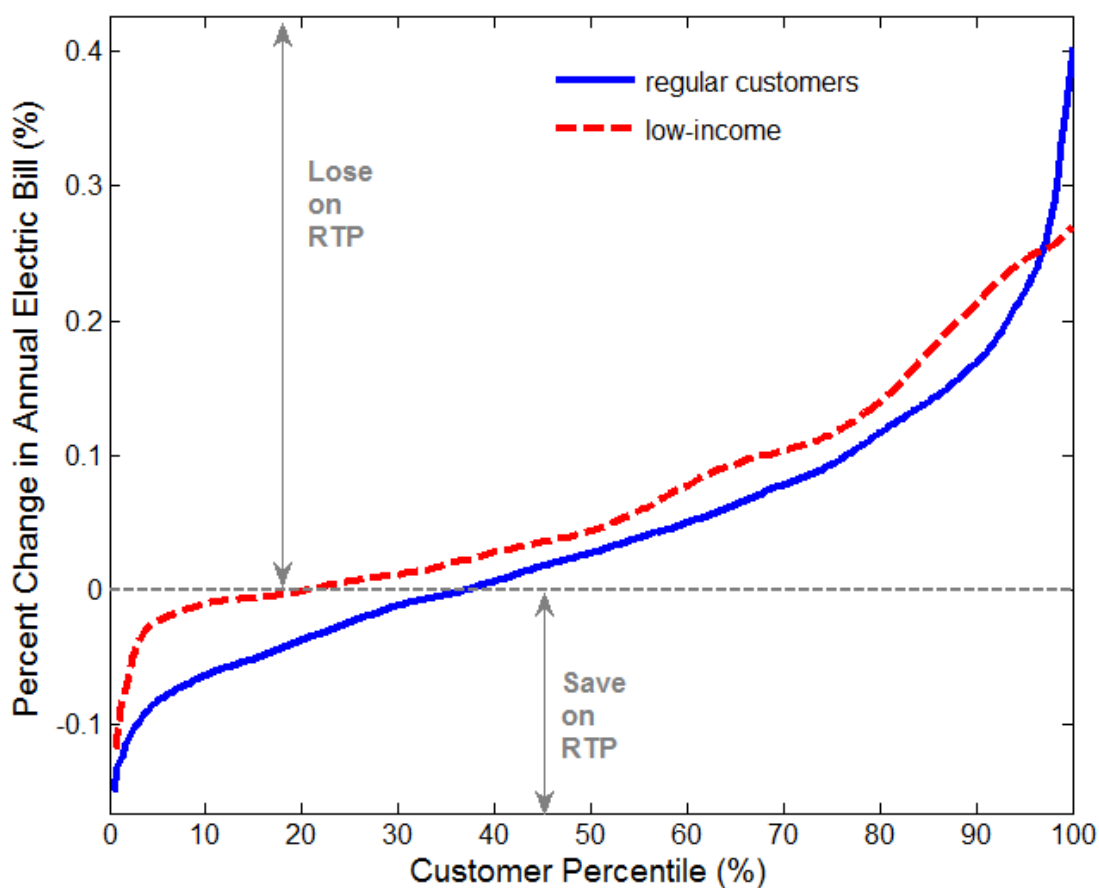


Figure 6: Distribution of bill change for low income customers and the remaining customers.

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### 3.4 Customer Class

Figure 7 shows the distributions for bill change by the four customer classes and table 4 shows the percent of customers in each customer class who would have saved under RTP. Space heating customers (SFH and MFH are 5.5% of the population) tend to save the most under RTP because they are winter peaking, and price tend to be lower in the winter. SF customers tend to save more than MF customers which is correlated with the fact that they tend to use more power.

Table 4: Percent of customers who would have saved under RTP by customer class

Customer Class	Percent of customers who would have saved under RTP [95% CI]
Single family (SF)	45 [40 49]
Multi-family (MF)	11 [8 14]
Single family, electric space-heat (SFH)	98 [96 100]
Multi-family, electric space-heat (MFH)	65 [62 69]

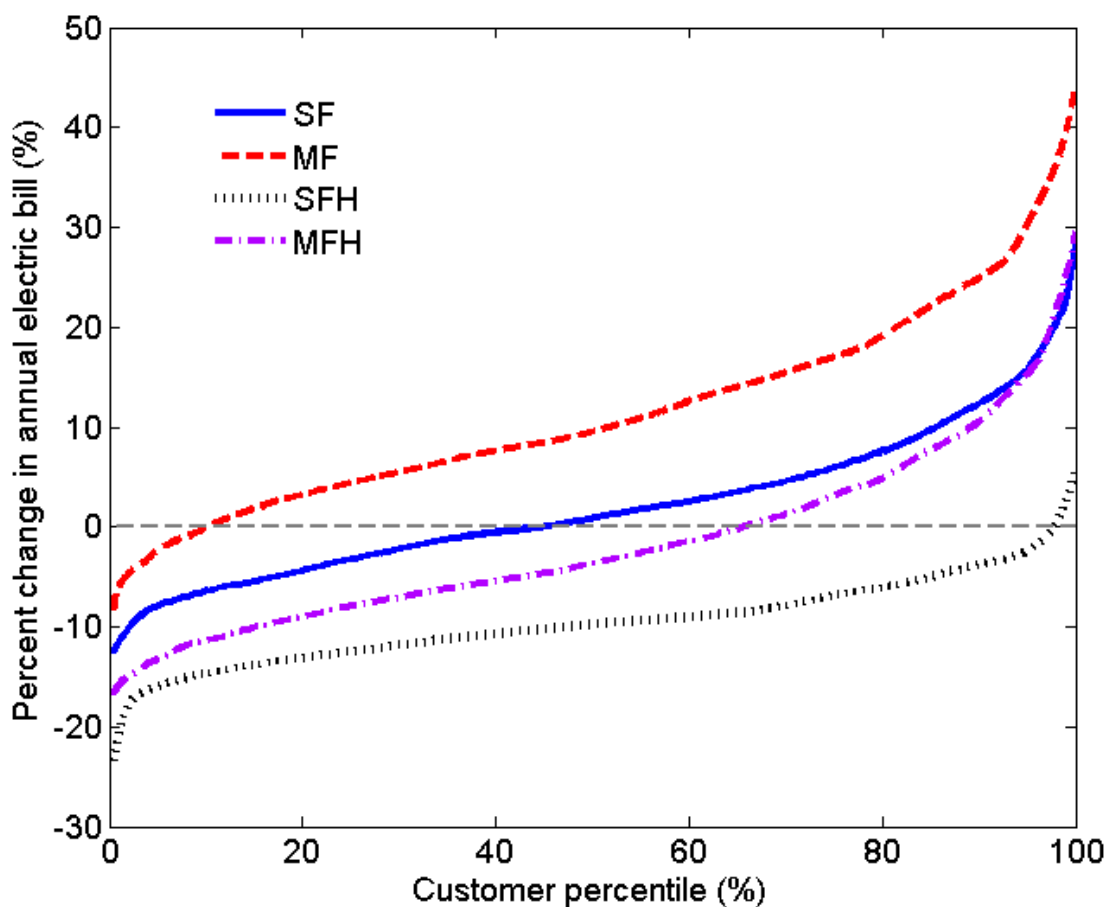


Figure 7: Distribution of percent change in annual electric bill under RTP compared to FR by customer class.



### 3.5 Comparison with other studies

In similar analyses Borenstein (2012) and Faruqui et. al. (2010) have different results. Borenstein analyzed distributional effects for opt-in CPP and TOU tariffs for Pacific Gas and Electric (PG&E) and Southern California Edison (SCE) customers and found that low consumption houses see bills decline under dynamic pricing, while high consumption households have higher bills. In an analysis of programs in the District of Columbia, Baltimore, Connecticut and California, Faruqui et. al. found that low income customers can benefit from dynamic pricing without changing behavior. However, the general result amongst all three analyses is the same: most consumers will see little impact to their electricity bills under dynamic pricing.

There are several possibilities for the divergences in our results. We use different regions in our analyses which will result in different usage and price patterns. Different weather in different regions will further change usage patterns. Borenstein's and Faruqui et. al.'s analyses focus on TOU and CPP which do not change prices across seasons, while RTP (in our example) has a significant seasonal cycle. Seasonal usage patterns dominate the overall cost shifting in our example, which is not present in the analyses with CPP and TOU. The finding that low-income consumers tend to save in the other analyses, while they tend to lose in our analysis is an artifact of the fact that low-income households tend to be low-consumption households.

## 4. ELASTICITY OF DEMAND

The objective of RTP for residential customers is to get an increase in economic efficiency by exposing customers to marginal cost. There is no guarantee of a response – the change in price must be large enough for customers to deem a response worthwhile, prices must be properly communicated and customers must have the means to shed or shift load, including: discretionary load, time, education and automated technology. There is evidence that customers do respond to real time rates. An analysis of the Ameren Power Smart Pricing program (an RTP tariff in Illinois) found an elasticity of demand of -0.043

(Violette and Klos 2009). The ComEd Energy Smart Pricing Program (RTP pilot) was found to have elasticities<sup>7</sup> ranging from -0.042 to -0.117 for different strata (Summit Blue 2007). However, these pilots have biases, including volunteer selection bias and intervention bias which may lead to a significant overestimation of the elasticities (Davis, et. al. 2012).

In this section we assume customers respond to increased marginal prices by lowering their electricity usage. Unlike the previous analysis, this is no longer a zero sum game – if some customers respond then there should be a net savings to society. There are several mechanisms through which customers can save: (1) if they reduce their load, then they are not charged the higher prices at that time for using power, (2) if customers shift load to a time when price is lower, they are charged the lower price, (3) if enough customers reduce load to reduce the marginal price, then all customers pay a lower price and (4) if enough customers reduce load to reduce the capacity needs for the region, then all customers pay lower capacity costs.

#### 4.1 Assumptions

We apply the same assumptions used in section 3 with some additions. We assume that customers respond with a non-linear price elasticity of demand. We assume that customers respond only when price exceeds a certain threshold:  $P > P_T$ . Below  $P_T$  we assume that consumers have a satisficing “deadband” – i.e. 5¢/kWh and 6¢/kWh are seen as the same price to a consumer and will not induce behavior change. We use  $P_T = 10¢/kWh$  and  $P_T = 14¢/kWh$  since ComEd customers chose one of these thresholds for high price notifications. We also assume that the ability to shed or shift load is weather dependent, since the major discretionary load for consumers is cooling/heating (Summit Blue 2007). We assume all customers shift load when temperature exceeds 80°F and space heating customers shift load when temperature is below 30°F. We assume that all ComEd residential customers respond to price, and collectively become price setters, meaning that a reduction in residential demand can reduce LMPs.

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<sup>7</sup> Note that elasticities in the Ameren and ComEd reports was calculated only using marginal price. We use the sum of marginal price for energy costs and all other average costs in elasticity calculations, since this reflects the prices customers actually pay. Because of this the same reduction in load reflects a lower elasticity in the ComEd and Ameren reports than in ours. We therefore use a wider range of elasticities in our calculations, to reflect the elasticities calculated in these reports, and a higher range for potential increases in elasticity of demand.

Table 5: Percent of time that price and temperature thresholds are exceeded.

	Temp < 30 °F	Temp > 80 °F	All temperatures
Price > 10¢/kWh	1.5%	2.6%	7.2%
Price > 14¢/kWh	0.3%	0.8%	1.6%

#### 4.2 Analysis: Stable Capacity Costs

We first assume that consumers are price setters on the energy market but that capacity costs remain constant. We do this to look at the distributional impact due to elastic demand on the energy market alone. Under elastic demand in the long run, supply would readjust (Borenstein, 2005), however we do not include a long-run equilibrium model. Instead we allow elastic demand to move along the actual supply curve for the ComEd node in PJM during 2007 and 2008 (see Appendix E).

The following is done to calculate bill differential when there is an elasticity of demand (more complete details can be found in Appendix F): New hourly consumption for each customer is calculated based on the assumed elasticity of demand,  $\epsilon$ . The resulting change in system wide demand for the ComEd node of PJM is then calculated. The LMP for that hour is recalculated using a non-parametric regression (Appendix E). Capacity obligations for each customer are calculated based on their new elastic usage. When applicable, new capacity charges are added in. The bills for RTP are then calculated using the new elastic usage, capacity obligation, LMP and capacity charge where applicable. FR bills are re-calculated using the original usages and prices, however we vary capacity in some scenarios to simulate the counterfactual where capacity charges decrease under RTP with respect to FR, due to lower peak demand under RTP. The bills are then differenced in the same manner as in section 3.

Figure 9 shows the total savings per customer as a function of elasticity of demand, when customers respond to prices above 10¢/kWh and 14¢/kWh. If elasticity is only -0.01 and customers respond when prices exceed 10¢/kWh, then savings amount to only \$6/customer-yr, or 0.5% of the average bill. With an elasticity of -0.5 (an upper bound, since this is much greater than the realistic estimates of elasticity under RTP), savings amount to \$63/customer-year, or 6% of the annual average

bill. The threshold at which customers begin to respond is important. If customers are responding with an elasticity of  $-0.2$  above  $14\text{¢/kWh}$ , they can increase savings by over  $80\%$  by also responding when prices are  $10 - 14\text{¢/kWh}$ .

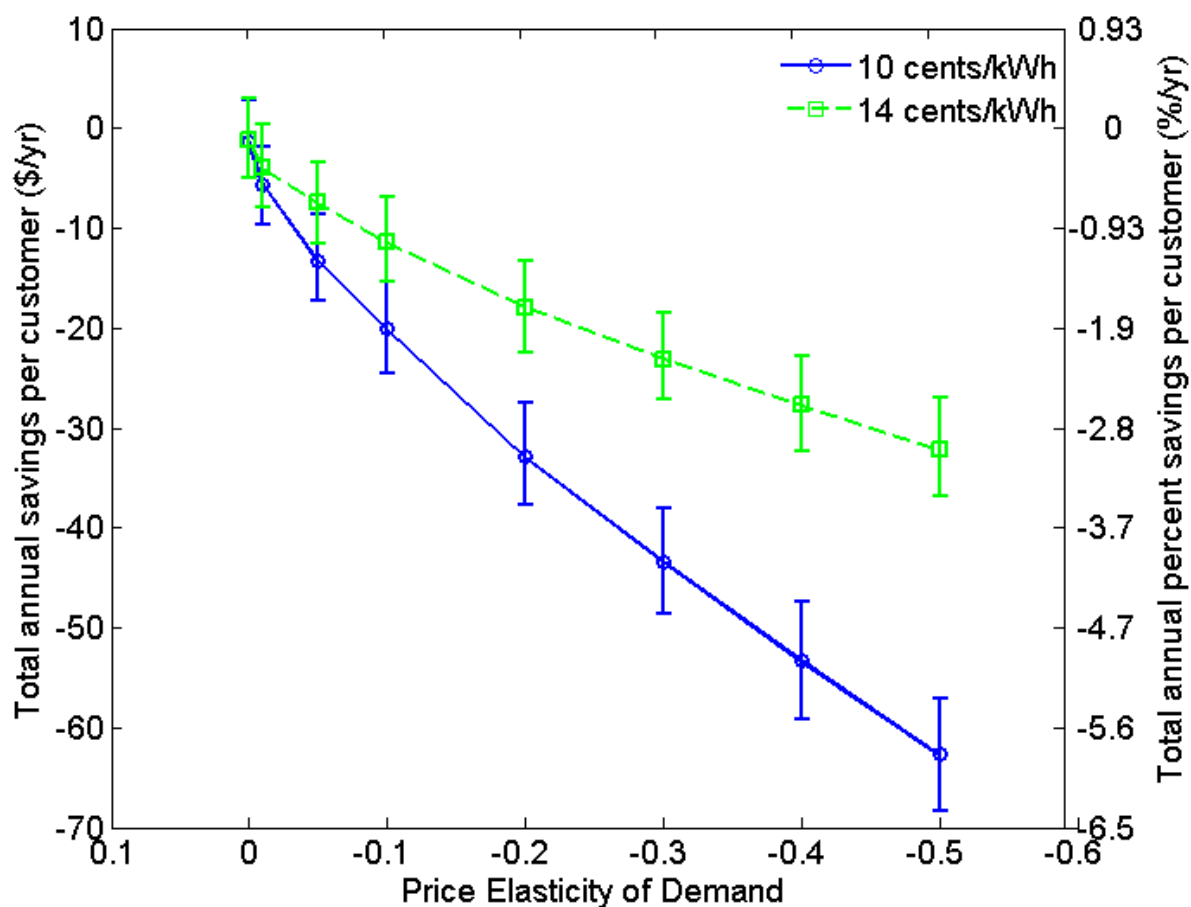


Fig 8: Annual savings per customer in both absolute dollars and as a percentage of average bill, as a function of price elasticity of demand, for a price threshold of  $10\text{¢/kWh}$  and  $14\text{¢/kWh}$  with  $95\%$  confidence intervals.

Despite the fact that there is a net welfare gain for all customers with even the slightest elasticity, not all customers will directly see those savings. Figure 9 shows percentage of customers who see a net savings over the year for the scenarios in figure 8. It takes an elasticity of  $-0.2$  when customers respond above  $10\text{¢/kWh}$  for just half of the customers to see a net savings compared to what they would have paid

under FR. With an elasticity of  $-0.5$  (which is likely above the realistic range), only about 60% of customers see a net savings.

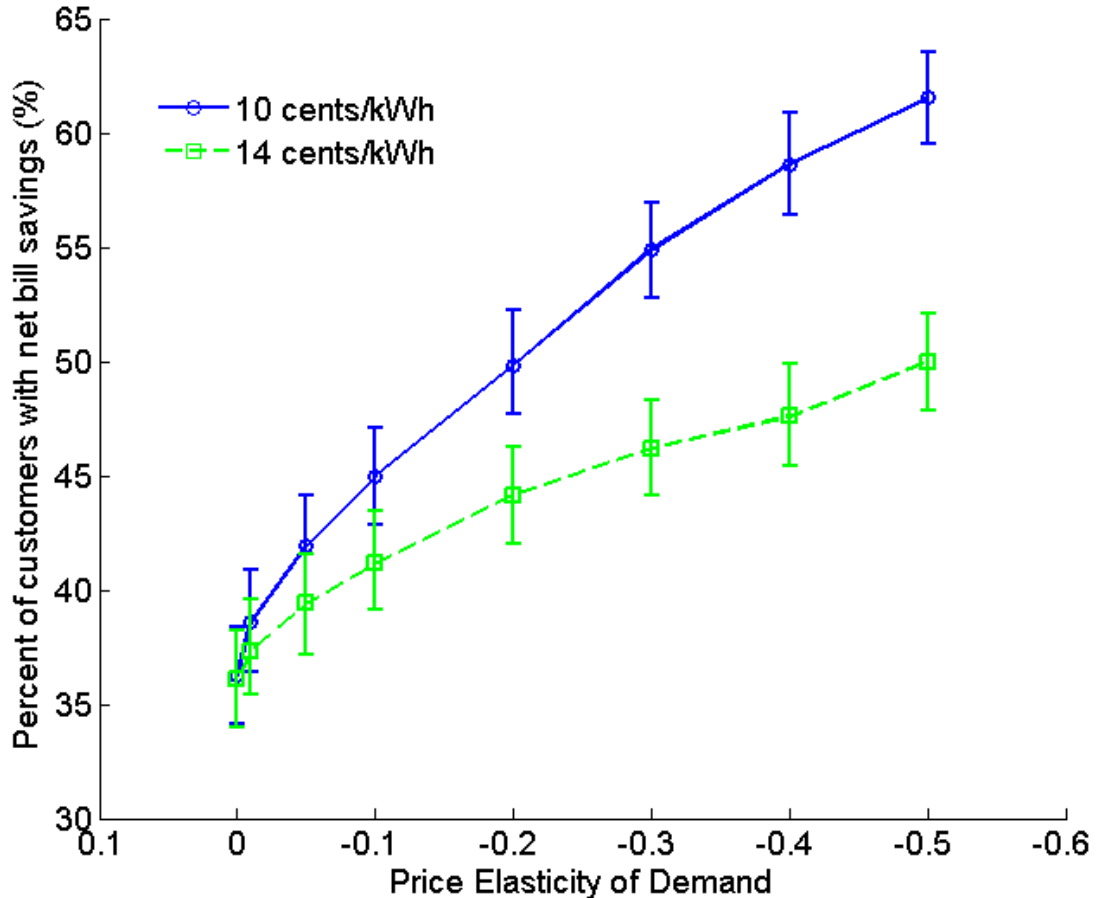


Figure 9: Percent of customers who would have a net savings in RTP compared to FR as a function of price elasticity of demand with 95% confidence intervals. The solid curve shows scenarios with a price threshold of  $10\text{¢}/\text{kWh}$  and the dashed line has a threshold of  $14\text{¢}/\text{kWh}$ .

#### 4.3 Analysis: Increasing Capacity Costs

We next allow capacity cost to vary under elastic demand. We assume capacity cost to be exogenous and do not include a long-run equilibrium model; we simply explore the distributional effects if capacity were to change by a given amount. We assume two scenarios. In the first scenario, capacity

prices increase equally for RTP and FR customers<sup>8</sup>. This is essentially what has happened for customers over the last several years. In early 2007, residential RTP customers in ComEd were paying \$0.09/kW-mth for capacity. The capacity price rose to \$5.70/kW-mth in June 2010, and at the end of 2011 was down to \$3.40/kW-mth. In the second scenario, price increases only for FR customers. This is to simulate the counterfactual, where capacity prices would have increased without elastic demand, however the decrease in demand due to the elasticity induced by RTP led to a reduction in necessary capacity and therefore a reduction in capacity prices under RTP.

Figure 10 shows the savings per customer per year for these two scenarios, with an assumed elasticity of -0.2 and a price threshold of 10¢/kWh. When capacity increases for RTP customers, and the counterfactual FR customers, RTP customer do save more, but the saving are moderate. A \$5/kW-mth increase in the capacity costs saves roughly an additional \$16/customer-yr, an increase of about 50%. When RTP customers avoid this increase however, marginal savings are significant: the same \$5/kW-mth increase in capacity costs saves an additional \$130/customer-yr, or nearly 400%.

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<sup>8</sup> The capacity charge is rolled into the supply charge for FR customers, so we increase the supply charge to that the total difference paid by all customers is equivalent to the total increase in capacity charge paid by all RTP customers with an elasticity of zero.

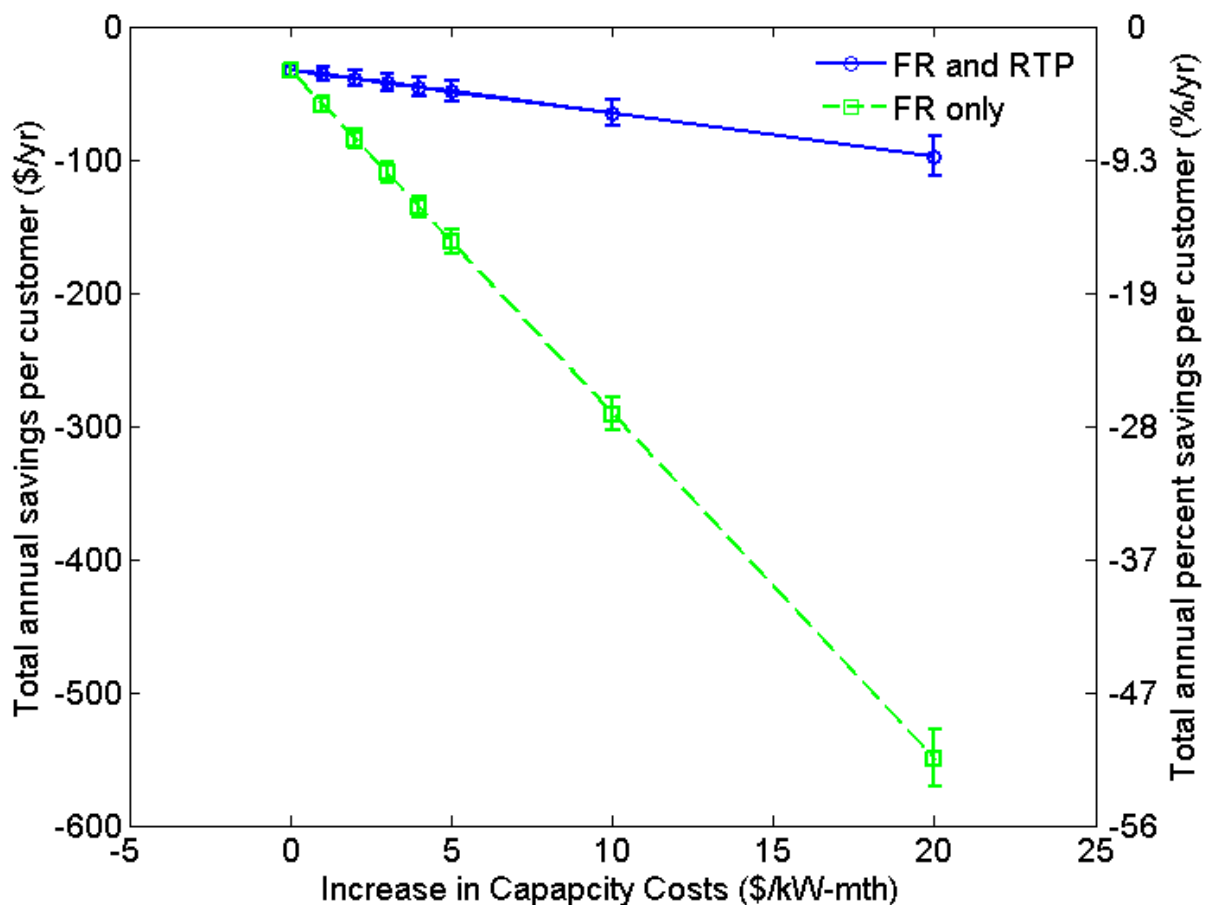


Figure 10: Savings per customer per year (absolute and percentage) as a function of increased capacity costs.

Even with additional savings of \$130/customer year, not all customers will directly see the savings. Figure 11 shows the percent of customers who save under the scenarios in figure 10. With no change in capacity costs, roughly 50% of customers directly save. An increase of \$5/kW-mth results 83% of customers saving – a significant increase, but some customers still faces losses compared to what they would have paid under FR.

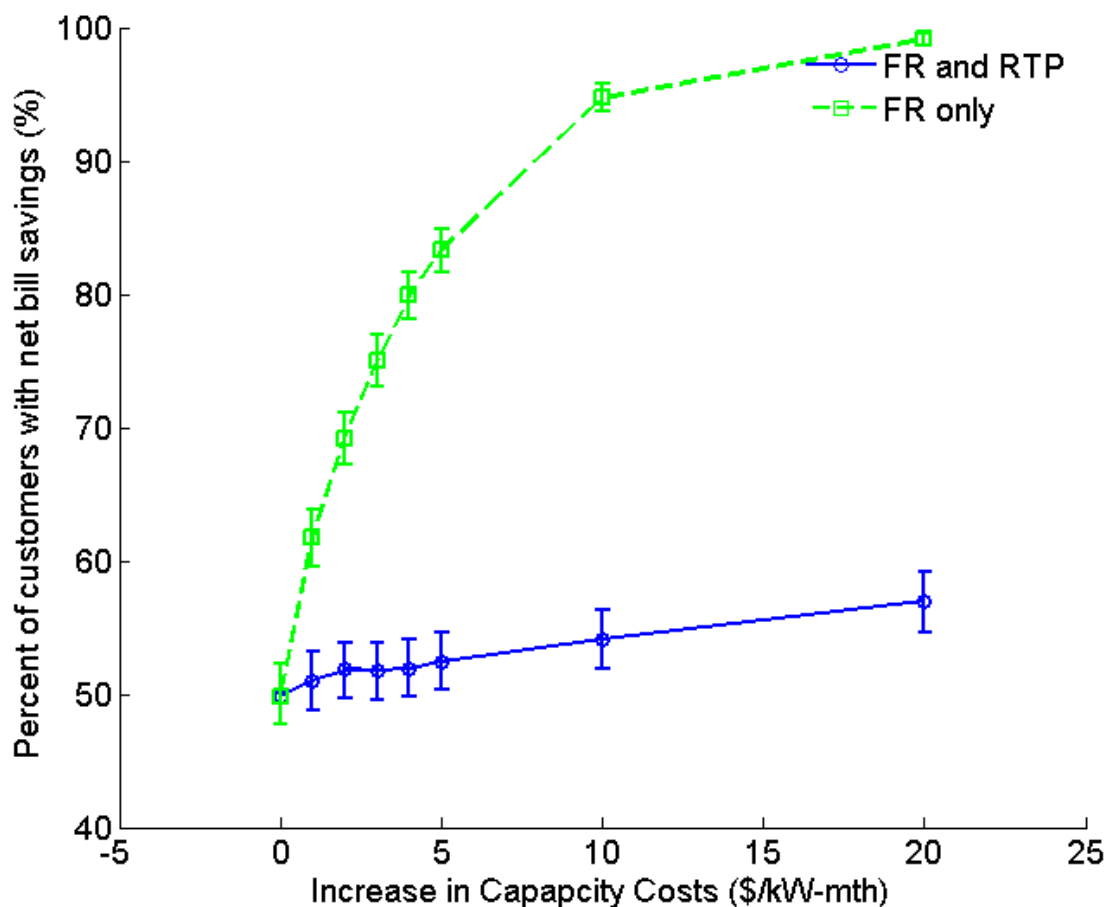


Figure 11: Percent of customers who would have a net savings in RTP compared to FR as a function of the increase in capacity costs, for a high temperature threshold of 80°F, low temperature threshold of 30°F and elasticity of demand of -0.2 with 95% confidence intervals. The solid curve represents the scenario where both RTP and FR rates see an increase in capacity costs, the dashed curve shows when only FR sees an increase in capacity costs, but RTP does not.

The patterns of which consumers save, are similar to the patterns in section 3. The customers with the largest average usages save the most money, and the customers with the smallest loads lose the most.

## 5. POLICY IMPLICATIONS AND DISCUSSION

RTP can bring efficiency to retail electricity markets and has the potential to bring a net welfare increase to consumers if they shift or curtail usage during peak times. However, many consumers will not save money in the short run, even if they have elastic demand from discretionary load, because they



would lose the cross-subsidy they receive under FR when switching to RTP. These customers tend to have smaller loads (which may imply less discretionary load, and therefore less elastic demand) and includes a greater proportion of low-income consumers. If there is a mass rollout of RTP, many of these consumers would still lose money in the short run even if they have elastic demand. In the particular case we explored, 50% of customers would still lose money in the short run, even if they had elasticity of -0.2 (which is higher than most estimates of elasticity under RTP).

There is a potential for major savings for all customers in the long run, from avoiding to build more capacity. If customers are able to cut peak demand and avoid increased capacity costs in the long run, then many more, or perhaps all customers can save money, however these customers may still see a net bill rise at first.

Policy makers who are considering implementing RTP must not just consider the net efficiency gains and net savings to consumers, but must also look at how these gains will be distributed, and consider that many consumers will actually incur losses relative to FR. Policy makers can consider giving RTP only to the portion of consumers who would contribute the most to peak shaving and will also see direct benefits, however this would be removing a large portion of those who provide the cross-subsidy under FR, pricing, and those being cross-subsidized would still see bill increases. Dynamic rate designs other than RTP, such as CPP, which focus on only changing prices during the hours when capacity is at the margins, and compensate consumers based on capacity costs only and not energy costs, may be a solution to this issue.

Policy makers also need to focus on how to communicate long run savings to consumers, since RTP can lead to very substantial savings in the long run if significant increases in capacity prices are avoided. This is a huge policy barrier however – it is difficult to tell consumers to bear an increase in electricity bills today to avoid an even larger increase in bills in several years.

This results in this paper are valid only for customers of ComEd during 2007 and 2008. They are not meant to be directly applied to other jurisdictions or times. We neglected to account for uncertainty in

price and demand. It is meant only to serve as a warning to policy makers that a similar analysis is necessary for their jurisdictions before the implementation of a dynamic pricing policy.

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## REFERENCES

- Alcott, Hunt (2011). "Rethinking real-time electricity pricing," *Resource and Energy Economics*, 33 820-842.
- Borenstein, S and Holland, S (2005). "On the Efficiency of Competitive Electricity Markets with Time-Invariant Retail rates," *RAND Journal of Economics*, 36(3):469-493.
- Borenstein, S., Jaske, M. and Rosenfeld, A (2002). "Dynamic Pricing, Advanced Metering and Demand Response in Electricity Markets," *Hewlett Foundation Energy Series*.
- Borenstein, Severin (2005). "The Long Run Efficiency of Real Time Pricing," *The Energy Journal*, 26(3): 93-116.
- Borenstein, Severin (2007a). "Customer Risk from Real-Time Retail Electricity Pricing: Bill Volatility and Hedgability," *The Energy Journal*, 28(2): 111-130
- Borenstein, Severin (2007b). "Wealth Transfers Among Large Customers from Implementing Real-Time Retail Electricity Pricing," *The Energy Journal*, 28(2), 2007: 131-150.
- Borenstein, Severin (2012). "Effective and Equitable Adoption of Opt-In Residential Dynamic Electricity Pricing," *Energy Institute at HAAS Working Paper 229*
- Commonwealth Edison Company (2006). Schedule of Rates for Electric Service. Commerce Commission Filing.
- Commonwealth Edison Company (2007). Schedule of Rates for Electric Service. Commerce Commission Filing.
- Davis, A., Krishnamurti, T., Fischhoff, B., Bruine de Bruin, W., (2012). Setting a standard for energy pilot studies: Guidelines for design, representation, and evaluation. Manuscript in preparation. Carnegie Mellon University: Department of Social and Decision Sciences and Department of Engineering and Public Policy.
- Faruqui, A and Sergici S (2010). "Household response to dynamic pricing of electricity: a survey of 15 experiments," *Journal of Regulatory Economics*, 38:193-225.
- Faruqui, A, Sergici, S and Palmer, J (2010). "The Impact of Dynamic Pricing on Low Income Customers," *Institute for Electric Efficiency Whitepaper*.
- Faruqui, Ahmad (2010). "The ethics of dynamic pricing," *The Electricity Journal*, 23(6): 13-27.
- Hirsch, Richard F (1999). *Power Loss*. Cambridge: MIT Press.
- Holland, S and Mansur, E (2006). "The Short Run Effects of Time-Varying Prices in Competitive Electricity Markets," *The Energy Journal*, 27(4): 127-156.
- PJM Interconnection (2009). *A Review of Compensation and Cost Elements in the PJM Markets*. Technical Review.

- Spees, K and Lave, L (2007). "Demand Response and Electricity Market Efficiency." The Electricity Journal. 20(3): 69-85.
- Spees, K and Lave, L (2008). "Impacts of Responsive Load in PJM: Load Shifting and Real Time Pricing." The Energy Journal. 29(2): 101-122.
- Summit Blue Consulting (2007). Evaluation of the Energy-Smart Pricing Plan: Final Report. Summit Blue Consulting, LLC, Boulder, CO.
- Violette, D and Klos, M (2009). Power Smart Pricing 2008 Annual Report. Summit Blue Consulting, LLC, Boulder, CO.

## APPENDIX

### A. ComEd Bills and Calculations

This appendix shows the ComEd residential bill breakdown for FR and RTP (table 7) with prices or prices ranges over 2007 and 2008 and major calculations used in this work including customer bills and bill difference. All information in this section comes from Commonwealth Edison Company (2006 and 2007).

Table 6: Indices used in calculations

Symbol	Description	Set
$i$	Customer	
$t$	Time, hourly resolution	
$r$	Real time price	
$f$	Flat rate price	
$p$	rate	$\{r, f\}$
$c$	Customer class	{single family, multi-family, single family space heat, multi-family space heat}
$m$	month	$\{Jan, \dots Dec \in y\}$
$y$	year	$\{2007, 2008\}$

Table 7: ComEd Residential Bill Breakdown

Component	Charge name	Charge range		Symbol
		Flat rate	RTP	
Electricity supply	Electricity supply charge	4-8¢/kWh	LMP -25 – 50¢/kWh	$ESC_{p,t,c}$
	Transmission service charge	.2-.8¢/kWh	0.2 – 0.8 ¢/kWh	$TSC_{p,t,c}$
	Capacity obligation	0	\$0.09–3/kWmt	$CO_{p,m}$
	Purchased electricity adjustment	-.1-2¢/kWh	-0.1 – 2¢/kWh	$PEA_{p,t}$
	Miscellaneous procurement charge	0	0.3¢/kWh	$MPC_{p,t}$
Delivery service	Customer charge	\$4.84/mt (mf), \$6.67/mt (sf)		$CC_c$
	Metering charge	\$2.21/mth		$MC$
	Distribution charge	~2¢/kWh		$DC_c$
	Meter lease	0	\$7.25/mt	$ML_p$
Taxes and other	Smart meter program	9¢/mth		$SMP$
	Environmental cost recovery	0.01¢/kWh		$ECR_t$
	Energy efficiency programs	0.147¢/kWh		$EEP$
	Franchise cost/state/municipal tax	varies – not included in calculation		

Note that the subscripts imply the variability of each variable. So  $ESC_{p,t,c}$  varies with the rate, time and customer class, while  $MC$  is constant. Some components of the bills, which are fixed rates, or part of the flat rate do change over the course of the 2 year period in question, however these changes occur in intervals of one month or greater. The only part of the bill that changes hourly is the electricity supply charge under RTP,  $ESC_{r,t,c}$ .

### Other variables

$U_{i,t}$  is the actual usage of customer  $i$  at time  $t$  in kWh.

$D_i$ , Demand for customer  $i$  in kWh/h, coincident with PJM and ComEd peak demand. Calculated based on the average usage for each customer during the 5 hours of highest demand for all of PJM and the 5

hours of highest demand for the ComEd node for each year. There are only 19 hours since one hour overlapped for PJM and ComEd demand.

$$D_i = \frac{1}{19} \sum_{t \in A} U_{i,t} \quad (1)$$

Where,

$$A = \{7/9/2007:1600, 8/8/2007:1400, 8/8/2007:1500, 8/8/2007:1600, 8/8/2007:1700, \\ 8/8/2007:1800, 8/7/2007:1600, 8/7/2007:1700, 8/7/2007:1800, 8/7/2007:1900, \\ 6/9/2008:1500, 6/9/2008:1600, 6/9/2008:1700, 6/9/2008:1800, 7/16/2008:1600, \\ 7/16/2008:1700, 7/16/2008:1800, 7/17/2008:1600, 7/17/2008:1700\}$$

(M/DD/YYYY:hhhh, hour ending, eastern prevailing time.).

Marginal price for customer  $i \in c$ , at time  $t$ , on rate  $p$  (\$/kWh):

$$M_{p,t,i} = ESC_{p,t,c} + TSC_{p,t,c} + PEA_{p,t} + MPC_{p,t} + DC_c + ECR_t + EEP \quad (2)$$

Fixed monthly price for customer  $i \in c$  on rate  $p$  for month  $m$  (\$/mth):

$$F_{p,m,i} = CO_{p,m} D_i + CC_c + MC + ML_p + SMP \quad (3)$$

Monthly bill for customer  $i$  on rate  $p$  for month  $m$  (not including taxes) (\$/mth):

$$B_{p,m,i} = F_{p,m,i} + \sum_{t \in m} M_{p,t,i} U_{i,t} \quad (4)$$

Annual bill for customer  $i$  on rate  $p$  for year  $m$  (not including taxes) (\$/yr):

$$B_{p,y,i} = \sum_{m \in y} B_{p,m,i} \quad (5)$$

Annual bill difference for customer  $i$  during year  $y$  had he been on RTP:

$$\Delta_{i,y} = B_{f,y,i} - B_{r,y,i} \quad (6)$$

Percentage difference in annual bill for customer  $i$  during year  $y$  had he been on RTP:

$$\delta_{i,y} = \frac{(B_{f,y,i} - B_{r,y,i})}{B_{f,y,i}} \quad (7)$$

## B. Revenue Neutral Calculation

The load weighted difference in FR and RTP prices are different for 2007 and 2008, so each year was made revenue neutral separately. The change to the FR marginal price (i.e. price per kWh) for 2007 to make it revenue neutral with respect to the RTP is  $-0.82\text{¢/kWh}$  with a 95% confidence interval of  $[-0.88, -0.76]$ . The change for 2008 is  $-0.34\text{¢/kWh}$  with a 95% confidence interval of  $[-0.41, -0.27]$ . Figure 12 shows the distribution for each year separately and both years together along with a 95% confidence interval for both years. It is difficult to make out the plots individually since they are statistically indistinguishable at the 95% confidence interval. For ease of presentation, results for 2007 and 2008 are shown together throughout the paper. The implications do not change by separating the years.

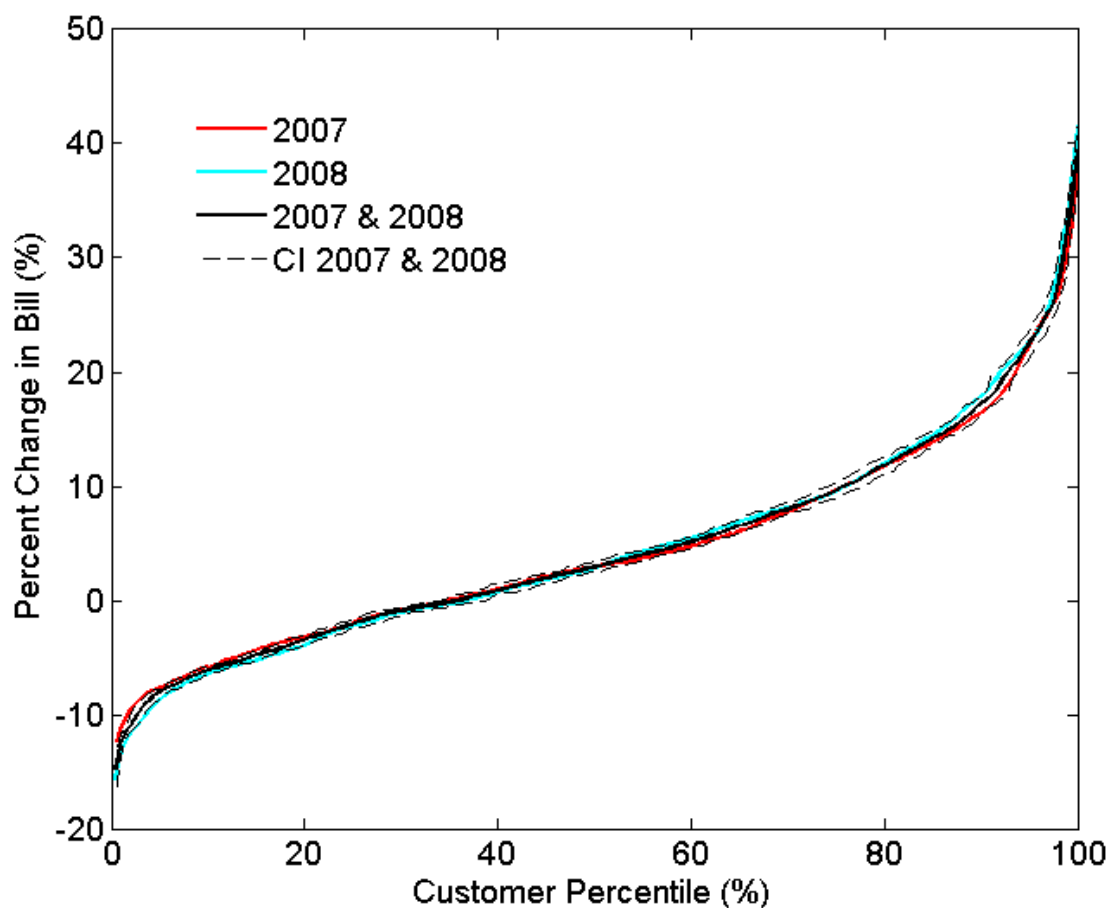


Figure 12: The distribution for changes in bill for 2007, 2008 and both years together and a 95% confidence interval for both years together.

### C. Bootstrap technique

Since the sampling rate was different for each of the 4 customer classes, bootstrapping was used to get statistics and distributions with confidence intervals for the entire population. No inferences outside the range of the data are made.

The total sample size is  $N$ . For each iteration of the bootstrap, the number of samples drawn from each customer class,  $\eta_c$ , is drawn from a *multinomial*( $n = N, p = [\pi_1, \pi_2, \pi_3, \pi_4]$ ) where  $\pi_c$  is the proportion of customer class  $c$  in the population.  $\eta_c$  observations are then randomly drawn with replacement from customer class  $c$ , for a total of  $N$  observations for each iteration of the bootstrap.

A statistic,  $\theta_i$  was then computed for each iteration,  $i$ , of the bootstrap. The mean  $\bar{\theta} = \frac{1}{N} \sum_{i=1}^N \theta_i$  is reported as the statistic. 95% confidence intervals are reported by ordering the statistics across iterations and extracting the 2.5<sup>th</sup> and 97.5<sup>th</sup> observations of the  $\theta_i$ .

Distributions were computed by binning the data into approximately 200 bins (this value was slightly varied depending on  $N$  so that there would be a discrete number of observations in each bin) for each iterations. The mean value across all iterations is reported for the distribution. Confidence intervals are reported using the same method as the statistics. The distribution was not sensitive to change in bin number in the range of 100 – 500 bins.

1000 iterations of the bootstrap were done. No improvement in accuracy was observed for more than 1000 iterations.

### D. Data cleanup

The raw data consisted of 37.8 million hourly electricity usage observations from 3082 customers. The data were cleaned to remove outlying or otherwise suspect data. When suspect data was removed, 35.5 million observations and 2962 customers remained. The following criteria were used to remove data:

- (1) Any usage observations of 0 were removed. The remaining data for that customer was left in.
- (2) Many customers had extreme values for a number of consecutive observations starting with their first observation. These data were deleted, however the remaining data for that customer was left in.
- (3) If a customer had any extreme observations after beginning consecutive observations were removed, all the data for that customer were removed.
- (4) ComEd filled in missing data for customers by alternating three values over the missing observations representing previous averages over different hours of the day for that customer. If more than 10% of a customer's data consisted of these average values, the entire customer was removed from the data.

Outliers are defined as any hourly observation exceeding these thresholds: 25 kWh/h for SF; 12 kWh/h for MF; 75 kWh/h for SFH; and 36 kWh/h for MFH.

Since electricity usage and price both have seasonal variations, it was important to analyze bill differences over an entire year for a customer. Therefore, of the customers who remained after suspect data was removed, only 1260 customers (consisting of 15.2 million total observations) who had at least one complete year of data (either complete 2007, complete 2008, or both) were used for the analysis.

To ensure that removing customers who did not have a complete year of data did not bias the dataset (for example, frequent movers would be removed disproportionately and may have different usage patterns) we performed an independent sample t-test with pooled variance between the mean usages for customers who had complete years of data and those who didn't (with suspect data removed). We split this by customer class and month. We were not able to reject the null hypothesis that the means were the same at the 95% confidence level for any customer class and month.

## **E. Non-parametric method for LMP calculation**

We re-calculate LMPs under elastic demand using the existing supply curve for the ComEd node of PJM during 2007 and 2008. We initially tried a parametric regression using all the data from the two year period. This gave us results that were sufficient for looking at price averages and statistics over certain periods of time, however these results were insufficient for comparing to single hours. For example, the model told us that for some hours, if demand dropped, price would increase. The model was giving correct information for a similar situation on average, however we reject that price would increase as



demand drops for the same exact hour. Instead we use a non-parametric method that essentially constructs a supply curve for small changes in demand for each hour individually. The algorithm follows:

$(D_t, P_t)$  = actual ComEd Demand  $D$  and System LMP  $P$  at time  $t$

$A = \{(D_i, P_i) \dots\}$  = set of  $(D_i, P_i)$  for  $i = t-x$  to  $t+x$  ( $x=7$ )

$D_0$  = new, unobserved ComEd Demand based on customer elasticity

$P_0$  = unobserved price corresponding to  $D_0$  – this is what we are trying to calculate

(a) Select 2 observations from  $A$  and assign to  $(D_1, P_1)$  and  $(D_2, P_2)$  such that:

1.  $D_i \leq D_0$  and  $\min(D_i - D_0)$  then assign to  $D_1$  and corresponding  $P_1$  to  $P_1$ . If no  $D_i \leq D_0$  then  $P_0 = \min\{P_i\}$
2. Assign  $D_i$  to  $D_1$  only if  $P_i \leq P_1$ . If  $P_i > P_1$ , then remove that  $(D_i, P_i)$  from  $A$  and go back to #1
3. Assign  $(D_i, P_i)$  to  $(D_2, P_2)$  such that  $\min(D_i - D_0)$  and  $(D_i - D_0) > 0$
4. Must have  $P_2 > P_1$ . If not then remove  $(D_2, P_2)$  from  $A$  and go back to #3.
5. If no  $P_i > P_1$  and  $D_i > D_0 > D_1$  then  $P_0 = \min\{P_i\}$

(b) If  $P_0$  has not yet been assigned and  $D_2 > D_0 > D_1$  and  $P_2 > P_1$  then assign  $P_0$  using linear interpolation as follows:

$$P_0 = P_1 + (D_0 - D_1) \frac{P_2 - P_1}{D_2 - D_1} \quad (8)$$

## F. Calculations for elasticity analysis

The following was done to calculate statistics for bill differences with an elasticity.

- a.  $N$  customers are randomly selected from the sample (total sample size =  $N$ ) with replacement so that the sample is representative of the population. These customers now constitute the set  $A$ .
- b. The elasticity is applied to all customers in  $A$  during hours when the real time price exceeds a certain threshold and the temperature exceeds a certain threshold. It is also applied to customers with electric space heating during hours when the price exceeds a certain threshold and the temperature is below a different threshold.
- c. New system wide demand is calculated by summing the change in demand across customers, scaling this up from the sample size to the population size, and subtracting it from the actual total demand during that hour.
- d. A new price is calculated for each hour based on the new system wide demand, using linear interpolation (see below for the algorithm).
- e. New capacity obligations are calculated for each customer by averaging their new, elastic usage during the 10 peak hours of the year (customers pay (capacity obligation in kW)X(capacity price in \$/kW-mth) each month)
- f. Flat rate bills are calculated based on non-elastic usage and RTP prices are calculated based on elastic usage, new capacity obligation and the new price for each customer in  $A$ .
- g. The difference between the FR and RTP is then calculated and summed for the total savings
- h. (a) – (g) is repeated 1000 times. Statistics on the sum calculated in (g) are reported by taking the mean as the point estimate and the 2.5<sup>th</sup> percentile and 97.5<sup>th</sup> percentile of the ordered sums as the

95% probability interval. A distribution of bill differences is made by averaging across savings for each observation (ie ordering customers by savings, then averaging the customer with the most savings for every bootstrap iteration, the customer with the 2<sup>nd</sup> to most savings across every iteration, etc.)