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Essays in Energy Economics

by

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Committee in charge:

Professor Peter Berck, Co-Chair
Professor Meredith Fowlie, Co-Chair
Professor Stefano DellaVigna
Professor Sofia Berto Villas-Baos

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Abstract

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In this dissertation I explore two aspects of the economics of energy. The first focuses on consumer behavior, while the second focuses on market structure and firm behavior.

In the first chapter, I demonstrate evidence of loss aversion in the behavior of households on two critical peak pricing experimental tariffs while participating in the California Statewide Pricing Pilot. I develop a model of loss aversion over electricity expenditure from which I derive two sets of testable predictions. First, I show that when there is a higher probability that a household is in the loss domain of their value function for the bill period, the more strongly they cut back peak consumption. Second, when prices are such that households are close to the kink in their value function – and would otherwise have expenditure skewed into the loss domain – I show evidence of disproportionate clustering at the kink. In essence this means that the occurrence of critical peak days did not only result in a reduction of peak consumption on that day, but also spilled over to further reduction of peak consumption on regular peak days for several weeks thereafter. This was similarly true when temperatures were high during high priced periods. This form of demand adjustment resulted in households experiencing bill-period expenditures equal to what they would have paid on the standard non-dynamic pricing tariff at a disproportionate rate. This higher number of bill periods with equal expenditure displaced bill periods in which they otherwise would have paid more than if they were on standard pricing.

In the second chapter, I explore the effects of two simultaneous changes in minimum energy efficiency and Energy Star standards for clothes washers. Adapting the Mussa and Rosen (1978) and Ronnen (1991) second-degree price discrimination model, I demonstrate that clothes washer prices and menus adjusted to the new standards in patterns consistent with a market in which firms had been price discriminating. In particular, I show evidence of discontinuous price drops at the time the standards were imposed, driven largely by mid-low efficiency segments of the market. The price discrimination model predicts this result. On the other hand, under perfect competition, prices should increase for these market segments. Additionally, new models proliferated in the highest efficiency market segment following the standard changes. Finally, I show that firms appeared to use different adaptation strategies at the two instances of the standards changing.

To my husband

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Chapter 1: Loss Aversion and Time-Differentiated Electricity Pricing

Charging a static price for retail electricity in the face of wholesale price volatility and demand fluctuations can result in short run shortages, as well as over-investment in, and under-utilization of, production capacity in the long run (Borenstein, Jaske, and Rosenfeld, 2002). Several dynamic pricing mechanisms have been designed to strengthen the connection between wholesale and retail prices, particularly at peak demand times of day. The simplest of these is Time of Use (TOU) pricing, wherein a low price is charged during off-peak hours, and a higher price charged during peak hours. A further extension of this concept is Critical Peak Pricing (CPP), wherein prices are set similarly to a TOU tariff, but the utility has the ability to charge a third, higher, price for peak consumption during a limited number of critical days when demand forecasts are particularly high. This improves upon TOU pricing by providing the utilities with a tool to be used when demand projections approach the capacity constraint of the system (Borenstein, Jaske, and Rosenfeld, 2002).[1]

The value of these time-differentiated pricing mechanisms is to both reduce the risk of demand outstripping supply in the short run, and reduce over-expenditure on new capacity in the long run. A study conducted for Southern California Edison found that demand response mechanisms, dynamic pricing being one, could result in up to 8% reductions in peak demand. Edison's highest capacity circuit at the time of the study in 2005 was 13 megawatts, and cost estimates for expansion of transmission and distribution ranged from $100 per kilowatt-hour (kWh) to $3000 per kWh. A back of the envelope calculation suggests that, if demand response were implemented to reduce peak demand by 8%, then the equivalent cost of forgone new capacity could be as much as $3.1 million (Kingston and Stovall, 2005).

In pilots conducted throughout the nation, of the various dynamic pricing mechanisms tested, CPP tariffs tend to be the most effective at reducing peak demand (Faruqui, 2010). While dynamic tariffs in general are designed to influence consumption behavior through a simple price-response mechanism based on standard economic assumptions of consumer rationality and unbiasedness, the psychology and economics literature may contribute insights into why CPP tariffs in particular are so effective.[2] One particular contribution from the psychology and economics literature – loss aversion – is most likely to be a factor in patterns of consumption behavior on a dynamic pricing tariff.

[1] Other dynamic pricing structures have been developed beyond CPP and TOU. These include Real Time Pricing tariffs (RTP) wherein the electricity price varies continuously throughout the day in response to wholesale price fluctuations, and Peak Time Rebate (PTR) tariffs which are similar to a CPP tariff except the incentive to reduce peak consumption during critical days comes in the form of rebates for forgone consumption rather than a higher price.

[2] In this work I examine one of many possible intersections between the literature on demand-side management of electricity markets on the one hand, and the psychology and economics literature on the other. Some previous studies have also sought to bridge these two fields. Hartman, Doane, and Woo (1991) demonstrate evidence of a wedge between consumer willingness to accept and willingness to pay for changes in electricity service reliability. Another example is the research of Allcott (2011), Ayres, Raseman, and Shih (2009) and Costa and Kahn (2010) into social norms and electricity conservation using the Opower billing mechanism. Finally, there is the theoretical work by Tsvetanov and Segerson (2011) exploring the role of temptation and self-control in underinvestment in energy conserving durable goods.

I find evidence that loss aversion is apparent in the electricity consumption behavior of households participating in a CPP dynamic pricing experiment. I outline a model of loss aversion over electricity expenditure and test predictions from this model. Loss aversion is a feature of reference-dependent utility, and suggests that consumers experience a larger impact to their utility from a loss relative to a gain. Loss aversion is relevant for dynamic pricing because, as prices change and consumers experience shocks to their demand for electricity, they incur expenditure higher than they are used to (a loss) in some bill periods, and lower than they are used to (a gain) in others. They will modify their consumption in predictable and policy relevant ways in order to avoid high losses and to enjoy gains. One of the predictions from the model I develop is that households will reduce consumption of high-priced electricity measurably more so if they are more likely to be in the loss domain of their value function rather than in the gain domain; I find consistent evidence that consumers reduce their consumption in high-priced peak hours more so if there is a higher probability they will be incurring a loss that bill period. A second prediction from the model is that levels of consumption will disproportionately cluster monthly expenditure at the kink in the value function where there is zero loss or gain; I show evidence of disproportionate clustering at the kink in the reference-dependent value function, particularly when prices are structured in such a way as to place households close to the kink and would otherwise have skewed their expenditure into the loss domain.

This paper will proceed as follows: I discuss the data in Section 1.1 before presenting the model in Section 1.2 because the dynamic pricing structure described in the data section motivates the model; Section 1.3 presents the estimation strategy and results; Section 1.4 discusses some alternative hypotheses, and Section 1.5 concludes.

1.1 Data

The data are from the California Statewide Pricing Pilot (SPP). This pilot was a collaboration between the California Energy Commission (CEC) and three of the state's largest electric utilities: Pacific Gas & Electric (PG&E), Southern California Edition (SCE), and San Diego Gas & Electric (SDG&E). The data consist of observations between roughly July 2003 and October 2004 of five groups: CPP High Ratio, CPP Low Ratio, TOU High Ratio, and TOU Low Ratio treatments, and a control group.[3] The control group was unaware that an experiment was being conducted, and were charged a standard time-invariant price for electricity. I use the term "reference price" to refer to the price control households faced, which is the same as the price treatment households had been facing prior to the experiment, and would revert to if they dropped out of the experiment. I focus primarily on the two CPP treatments (described below), while using the TOU treatment groups and the control group as counterfactuals.

The two CPP treatments tested a CPP tariff in which a relatively high price was charged for peak electricity – 2pm to 7pm on non-holiday weekdays – and a relatively low price

[3]Several different treatment groups were recruited for the pilot, but for this project I focus on this subset of these treatment groups. Within the documentation of the experiment, the treatment groups I used were the two CPP-F treatments and the two TOU treatments. I refer interested readers to previous analyses of this pilot for more detail on the other treatments (Herter, 2007; Faruqui and George, 2005; CRA, 2005).

was charged for off-peak electricity. Additionally the utility could call a limited number of critical peak days per season – announced the preceding day – wherein a precipitously high price was charged during peak hours. A total of twelve critical peak days were called during each of the summer phases (May through October) and a total of three were called during the winter months.[4] The choice to call a critical peak day depended on a variety of factors including weather forecasts, system capacity and reliability, and the limit to the number of critical peak days that could be called during the season. Utilities could only call critical peak days on non-holiday weekdays, but there was an attempt to call critical peak days on a variety of days of the week within that constraint during the experiment. During the first summer of the experiment (2003) all critical peak days that were called were non-contiguous, then in the second summer there were three sets of two or more proximate critical peak days called in order to see if households reacted differently to critical peak days if they came in a string (CRA, 2005).

The two TOU treatments tested a TOU pilot tariff in which a relatively low price was charged for off-peak electricity and a relatively high price was charged for peak electricity, with no critical peak feature. In the case of both the CPP and TOU tariffs, all consumption on weekends and holidays was charged at the low, off-peak price. Figure 1.1 depicts the prices for the two CPP treatment groups for non-CARE[5] PG&E customers over the course of the pilot to give a sense of the way prices were structured in the experiment, and to show the difference between the two CPP treatments.

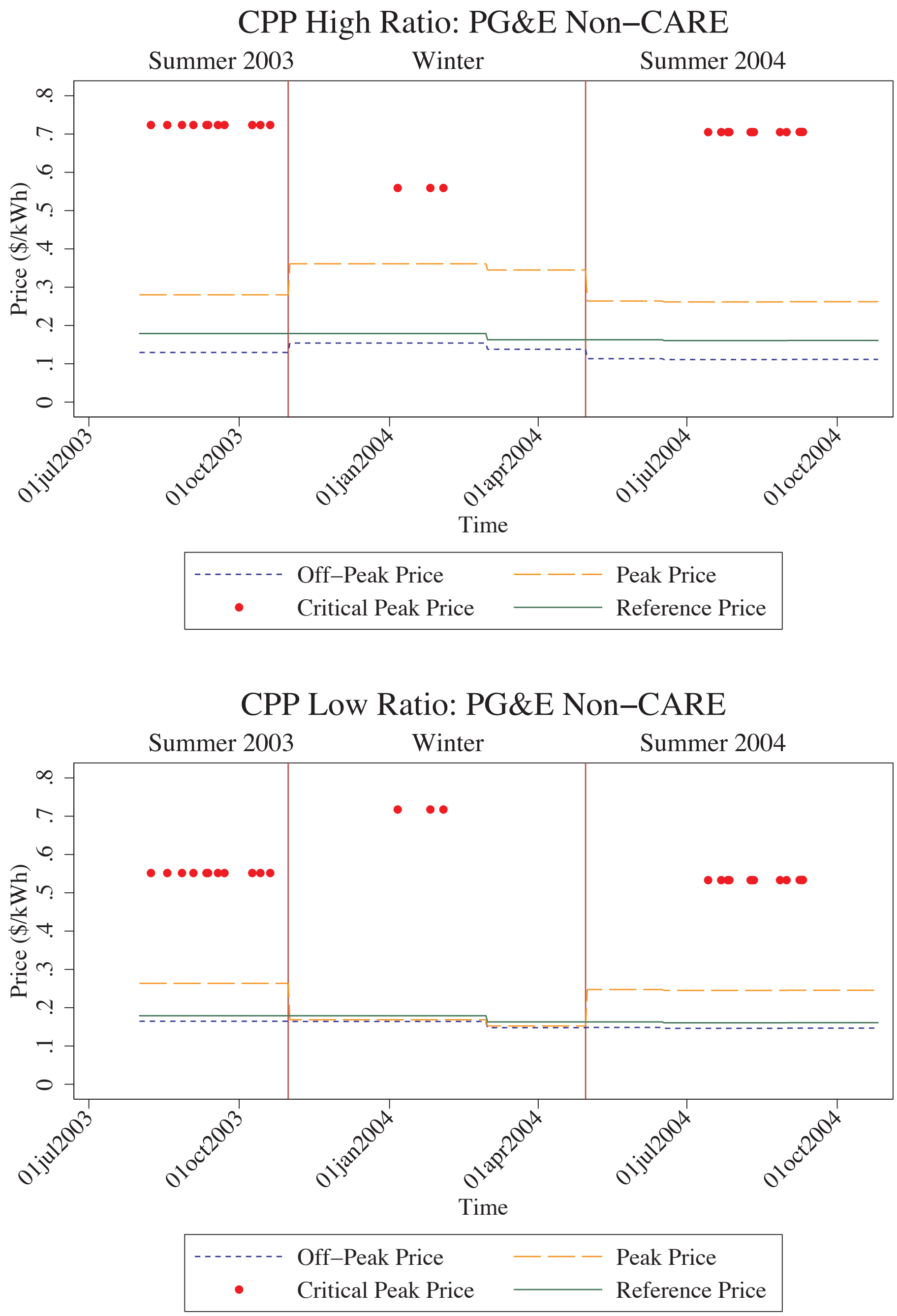
The two CPP treatments were referred to as the CPP Low Ratio (CPPL) treatment and CPP High Ratio (CPPH) treatment. The only difference between these treatments can be seen in Figure 1.1. Namely, for the CPPH group during the summer, treatment households faced a relatively high spread between the reference price and critical peak price, as well as the reference price and off-peak price, but a relatively low spread between the regular peak price and reference price. Then in the winter, the spreads for the CPPH treatment's between the reference price and off-peak, as well as critical peak, prices shrank, while the spread for the regular peak price and reference price expanded. On the other hand, for the CPPL treatment, the spread between the reference price and off-peak price was relatively small, remained constant across both the summer and winter pricing periods. The spread between the critical peak price and reference price was smaller in the summer than the winter, and the regular peak price was above the reference price in the summer, but dropped down to the off-peak price in the winter. The critical peak prices are represented as points in the figures in order to demonstrate the frequency and timing of critical peak days. The vertical lines in Figure 1.1 represent the dates on which the pricing changed from summer to winter pricing or vice versa.[6]

[4]This was true for PG&E and SDG&E but SCE shifts from summer to winter pricing slightly earlier than the other two utilities, so three of the CPP days called that were in the summer of 2003 for the other two utilities, were actually in the winter pricing phase for SCE.

[5]CARE stands for California Alternate Rates for Energy and is a program designed to provide price relief to low income households.

[6]A table detailing all the experimental prices can be found in Appendix A.1.

Figure 1.1: CPP Treatment Prices



Note: This figure depicts the experimental tariff faced by CPPH (top panel) and CPPL (bottom panel) treatment non-CARE households in the PG&E service territory during the SPP experiment. "Reference Price" refers to the price charged to the control households. The frequency of critical peak pricing days is depicted in the points demonstrating the "Critical Peak Price." The prices depicted here, and used throughout this paper, are the average prices (averaged across the block rate tiered electricity pricing structure).

I obtained data on all prices by referring to the historic advice letters submitted by the three utilities to the California Public Utility Commission. California has an increasing block rate pricing structure for electricity and the dynamic treatment prices consisted of a series of surcharges or credits overlaid onto this block rate structure. Because the theory of loss aversion used to motivate this analysis is primarily interested in relative prices (particularly relative to the reference price) and the surcharges and credits are constant across the tiers, the block rate structure is less relevant. Additionally, previous research has shown that customers are not always aware of, and do not generally respond to, the marginal price in their block rate structure. Rather, customers generally respond to an averaged price Ito (2012). I therefore conduct the analysis using the flat average price (averaged across the tiers) as a measure of the prices faced by the households. It is this average price that is plotted in Figure 1.1 and reported in the table in Appendix A.1.

The data include detailed electricity usage at 15 minute increments, which I identify as peak or off-peak usage, and aggregate up to the daily or bill period level. In addition, each household was matched to one of 56 weather stations, from which hourly average humidity and temperature were recorded. I average the temperature data over the peak and off-peak hours and construct a degree-hour measure of temperature within each of these time-periods for each day. This measure is constructed similarly to the more commonly used degree-day measure, but separately for the peak and off-peak periods each day.[7]

Finally, there are two main problems with the data from this experiment. First, there was some concern that when this pilot was initiated, households were unclear as to when precisely the experimental pricing started (Letzler, 2010). To avoid potential additional noise in the data, I drop observations from July 2003 (the initial month of the experiment). Second, the experimental design with respect to the comparability of the treatment and control groups was problematic. In particular, the treatment groups were recruited to participate while the control group was randomly selected from the population. This introduces an issue of selection into treatment and makes it likely that the control and treatment groups are systematically different in important ways. I do use the control group as a comparison group in this paper, but I also run the same analyses using the TOU treatment groups as a comparison group for the CPP treatment groups. This limits the external validity of the results further, but strengthens the comparability of the two groups in some ways, as they both selected into treatment. Some additional data cleaning determinations were made as I prepared the data for analysis. Appendix A.2 outlines what was done, as well as presents some robustness check variations of the primary regressions reported in the paper to test the relevance of some of the data irregularities, none of which significantly change the results.

Table 1.1 shows summary statistics for the relevant variables used in this analysis. Looking first at the two variables "Peak kWh per Day" and "Off-Peak kWh per Day," note that

[7]The degree-hour temperature measure is constructed in the following way: $Temp_{op,t} = |Mean\,(Temp_{h\in op,t}) - 65|$ and $Temp_{p,t} = |Mean\,(Temp_{h\in p,t}) - 65|$, where $Temp_{op,t}$ is the degree-hour temperature measure during off-peak hours on day t, $Temp_{p,t}$ is the same measure but for peak hours on day t, $Mean\,(Temp_{h\in op,t})$ is hourly average temperature during the off-peak hours of day t and $Mean\,(Temp_{h\in p,t})$ is the same for peak hours on day t . When temperature is higher than 65 degrees (fahrenheit) on average the cooling degree-hour measure of temperature is the amount that the average temperature is above 65 degrees . Conversely, when the temperature is below 65 degrees on average the heating degree-hour measure is the amount that the average temperature is below 65 degrees.

the table presents the mean and standard deviation of these measures *during the treatment period*. As one would expect, the treatment groups used less peak electricity on average than the control group during the experiment, and even at this aggregate level the difference is marginally significant. This might reflect both the treatment effect of the pricing differential and the selection effect mentioned above. Of note is that the off-peak electricity consumption is not statistically significantly different between the four groups at this aggregate level. This suggests broadly that the treatment did not evidently induce a large amount of consumption shifting from peak to off-peak, the implication of which, disregarding the selection effect, is that the own-price elasticity of off-peak consumption, as well as cross-price elasticity between peak and off-peak consumption, are not large. This is further confirmed in the analysis to follow. The "Bill Total" variable is the monthly total usage expenditure on electricity. Of note is the degree to which not only is the average expenditure on the CPP treatments lower then that of the TOU and control groups, but the standard deviation is actually lower as well. This could be due to the way in which the treatment tariffs were constructed, but could also be due to the behavior of the groups while in treatment.

In terms of the comparability of these four groups, note that the average kWh per Day pre-treatment usage measured in 2002 is very close, and not statistically different, between all four groups. Additionally, the average peak and off-peak temperatures, as measured in degree-hours, are not statistically significantly different between all four groups. Therefore, these four groups are comparable in terms of the pre-treatment average overall usage, and temperature levels faced during treatment. On the other hand, note that the CPP groups came mostly from PG&E and SCE, and the TOU group only represents customers from these two utilities, with no TOU treatment customers coming from SDG&E. The control households are biased slightly towards PG&E as compared to the other two utilities. Additionally, the share of observations in each climate zone differ somewhat between the treatment groups. Therefore, because the treatment groups selected into treatment there are reasons to be concerned about the comparability of the control group to the treatment groups. On the other hand, in terms of pre-treatment average daily usage, and weather, the control group appears to be comparable to the treatment groups. The TOU group is used as a counterfactual in this analysis in addition to the control group in order to account for some of the potential bias introduced by the selection into treatment, however, the TOU group differs from the CPPH and CPPL groups based on observables (as they were much more likely to come from the PG&E region, which means they are more likely to be from Northern California relative to the treatment groups). For this reason I choose to use the control group as the primary counterfactual, and present results using the TOU group as the counterfactual as a robustness check.

Table 1.1: Summary Statistics

Treatment Groups of Interest	**CPP High Ratio**		**CPP Low Ratio**	
	Mean	Std. Dev.	Mean	Std. Dev.
Average kWh per Day in 2002†	22.809	14.875	21.638	13.423
Off-Peak kWh per Day*	16.796	12.718	16.487	12.021
Peak kWh per Day*	5.362	5.388	5.396	5.494
Bill Total*	88.024	68.490	87.559	69.437
Off-Peak Temperature (Degree-Hour Measure)*	8.691	6.361	8.611	6.287
Peak Temperature (Degree-Hour Measure)*	12.442	9.256	12.267	9.247
PG&E Customer	0.485	0.500	0.489	0.500
SCE Customer	0.424	0.494	0.411	0.492
SDG&E Customer	0.091	0.287	0.101	0.301
Climate Zone 1	0.097	0.296	0.098	0.297
Climate Zone 2	0.331	0.471	0.344	0.475
Climate Zone 3	0.366	0.482	0.348	0.476
Climate Zone 4	0.205	0.404	0.210	0.407
Number of Observations	115109		118640	
Number of Households	321		345	
Counterfactual Groups	**TOU**		**Control**	
	Mean	Std. Dev.	Mean	Std. Dev.
Average kWh per Day in 2002†	22.125	15.194	22.579	15.257
Off-Peak kWh per Day*	16.315	13.230	16.380	12.967
Peak kWh per Day*	5.468	5.823	6.158	6.588
Bill Total*	91.869	75.938	96.583	79.686
Off-Peak Temperature (Degree-Hour Measure)*	8.908	6.195	8.917	6.292
Peak Temperature (Degree-Hour Measure)*	12.074	9.427	12.418	9.678
PG&E Customer	0.624	0.485	0.547	0.498
SCE Customer	0.376	0.485	0.377	0.485
SDG&E Customer	0	0	0.076	0.265
Climate Zone 1	0.277	0.447	0.174	0.379
Climate Zone 2	0.224	0.417	0.274	0.446
Climate Zone 3	0.256	0.437	0.276	0.447
Climate Zone 4	0.243	0.429	0.276	0.447
Number of Observations	86590		152903	
Number of Households	240		418	

† Pre-Treatment

* During Treatment Period

Note: The two critical peak (CPP) treatments are the treatment groups of interest in this study. The experimental time of use (TOU) treatment groups and the control group are both used as counterfactuals. Off-Peak kWh per Day and Peak kWh per Day are usage levels during the experiment. Bill Total is the average total bill-period expenditure during the experiment.

1.2 Model

In this section I develop a model of electricity consumption utility and demand including reference-dependent preferences over expenditure on electricity. Kahneman and Tversky (1979) developed one of the most widely adapted models of reference-dependent utility, called Prospect Theory. Extensions of this original model have been developed; most notable among them is the concept that utility is derived not only from outcomes relative to a reference point (as proposed by Kahneman and Tversky), but over the level of the outcome as well (e.g. Sugden (2003); Köszegi and Rabin (2006)). While Kahneman and Tversky's original model consists of four features (reference-dependence; loss aversion; risk aversion over gains and risk seeking over losses, and differential probability weighting), I follow the example of much of the empirical literature[8] in this area and focus only on reference-dependence and loss aversion, while assuming no curvature of the reference-dependent portion of the value function – an assumption which is referred to as assumption A3′ by Köszegi and Rabin (2006) – and no differential weighting of probabilities.

Required for models of reference-dependence is an assumption that consumers "narrowly bracket," or assess their sense of gains and losses over some limited time frame. I assume that consumers narrowly bracket at the bill period level. This means that each bill period m (sometimes referred to here as month, for simplicity), each consumer i experiences either a gain or loss over the electricity expenditure incurred that month, in addition to the direct utility they obtain from the consumption of electricity.[9]

Given temperature during peak and off-peak hours along with other determinants of demand captured in the vector $\boldsymbol{x}_{im}$, the vector of off-peak and peak current electricity prices $\boldsymbol{p}_{im} = (p_{op,im}, p_{p,im})$, and income I_{im}, the consumer chooses their consumption vector of off-peak and peak electricity $\boldsymbol{y}_{im} = (y_{op,im}, y_{p,im})$ to maximize their value function,[10] shown in Equation 1.1. The parameters η and λ (described in more detail below) are the parameters capturing reference-dependence and loss aversion, respectively. The first term of Equation 1.1 is consumption utility over peak and off-peak electricity, the second term is utility over money, (or the numeraire good), and the final term is the reference-dependent portion of utility. In this model, the consumer has utility over monthly expenditure on electricity $\boldsymbol{y}'_{im} \cdot \boldsymbol{p}_{im}$ relative to a reference level of electricity expenditure, r_{im}.

$$\begin{aligned} U(\boldsymbol{y}_{im}; \boldsymbol{x}_{im}, r_{im}) =& u\left(\boldsymbol{y}_{im}; \boldsymbol{x}_{im}\right) + \left(I_{im} - \boldsymbol{y}'_{im} \cdot \boldsymbol{p}_{im}\right) \\ &+ \eta \begin{cases} \lambda\left(r_{im} - \boldsymbol{y}'_{im} \cdot \boldsymbol{p}_{im}\right) & \text{if } \boldsymbol{y}'_{im} \cdot \boldsymbol{p}_{im} > r_{im} \\ \left(r_{im} - \boldsymbol{y}'_{im} \cdot \boldsymbol{p}_{im}\right) & \text{if } \boldsymbol{y}'_{im} \cdot \boldsymbol{p}_{im} \leq r_{im} \end{cases} \end{aligned} \tag{1.1}$$

The consumer incurs a loss if their current expenditure on electricity for the bill period $(\boldsymbol{y}'_{im} \cdot \boldsymbol{p}_{im})$ is greater than their reference level of expenditure (r_{im}). If their current bill period expenditure is less than the reference level, then they experience a gain. The reference-dependent parameters are η and λ. The parameter η is the weight placed on the reference-dependent portion of utility relative to the direct consumption utility. It is assumed that

[8] An excellent summary and discussion of the literature can be found in DellaVigna (2009).

[9] Note that I use the terms consumer and household interchangeably throughout this paper.

[10] "Value function" is the term used to describe consumption utility plus reference-dependent utility.

$\eta \geq 0$ (where $\eta = 0$ means the consumer has no reference-dependent utility). The loss-aversion parameter is λ; it is assumed that $\lambda \geq 1$, and if $\lambda = 1$ then the consumer is not loss-averse – they care equally about gains and losses relative to their reference point – whereas $\lambda > 1$ means the consumer is loss averse, meaning losses relative to their reference point weigh more heavily in their utility than gains.

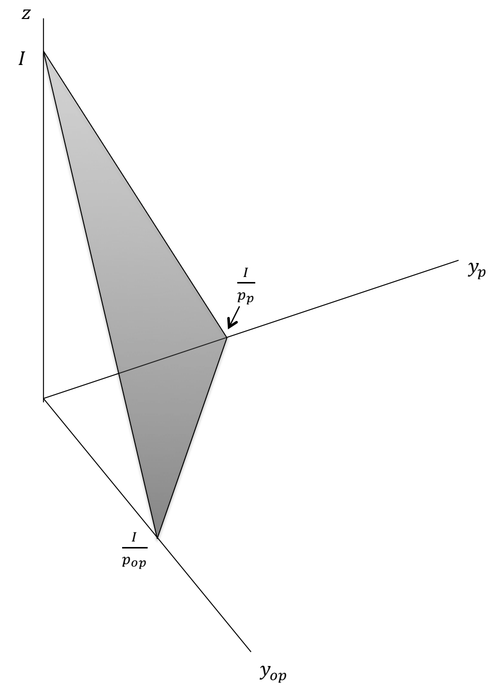
The question of the nature and adaptability of the reference point (r_{im}) is a major area of research in the literature, with many approaches and context-specific hypotheses. For treatment households in this experimental pricing pilot, I assume the reference point is based off of the standard time-invariant prices charged to the control households. Given this assumption, there are two logical reference points for bill-period electricity expenditure. First, one can imagine that the consumer's reference point is their expenditure for that bill period on the standard pricing structure given standard prices and their optimal consumption on the standard pricing structure, $r_{im}\left(\boldsymbol{p}_{r,im}\right) = \boldsymbol{y}_{im}\left(\boldsymbol{p}_{r,im}\right)' \cdot \boldsymbol{p}_{r,im}$. This is an exogenous reference point, meaning that it is not determined by current electricity consumption. Second, one can imagine that the consumer's reference point is what their current dynamic pricing structure consumption would cost at standard prices, $r_{im}\left(\boldsymbol{p}_{im}\right) = \boldsymbol{y}_{im}\left(\boldsymbol{p}_{im}\right)' \cdot \boldsymbol{p}_{r,im}$. This is an endogenous reference point in that it is set by the consumer's current consumption decision. The available data set lends itself most readily to the case of the endogenous reference point, because households received information about their "shadow" expenditure (precisely $r_{im}\left(\boldsymbol{p}_{im}\right)$) with their bill over the course of the experiment.[11] Additionally, the endogenous reference point case is the only one that is testable given available data. In Equation 1.2, I restate Equation 1.1 to reflect the assumption that $r_{im} = \boldsymbol{y}_{im}\left(\boldsymbol{p}_{im}\right)' \cdot \boldsymbol{p}_{r,im}$.

$$\begin{aligned} U(\boldsymbol{y}_{im}; \boldsymbol{x}_{im}, p_{r,im}) =& u\left(\boldsymbol{y}_{im}; \boldsymbol{x}_{im}\right) + \left(I_{im} - \boldsymbol{y}_{im}' \cdot \boldsymbol{p}_{im}\right) \\ &+ \eta \begin{cases} \lambda \boldsymbol{y}_{im}' \cdot \left(\boldsymbol{p}_{r,im} - \boldsymbol{p}_{im}\right) & \text{if } \boldsymbol{y}_{im}' \cdot \left(\boldsymbol{p}_{r,im} - \boldsymbol{p}_{im}\right) < 0 \\ \boldsymbol{y}_{im}' \cdot \left(\boldsymbol{p}_{r,im} - \boldsymbol{p}_{im}\right) & \text{if } \boldsymbol{y}_{im}' \cdot \left(\boldsymbol{p}_{r,im} - \boldsymbol{p}_{im}\right) \geq 0 \end{cases} \end{aligned} \tag{1.2}$$

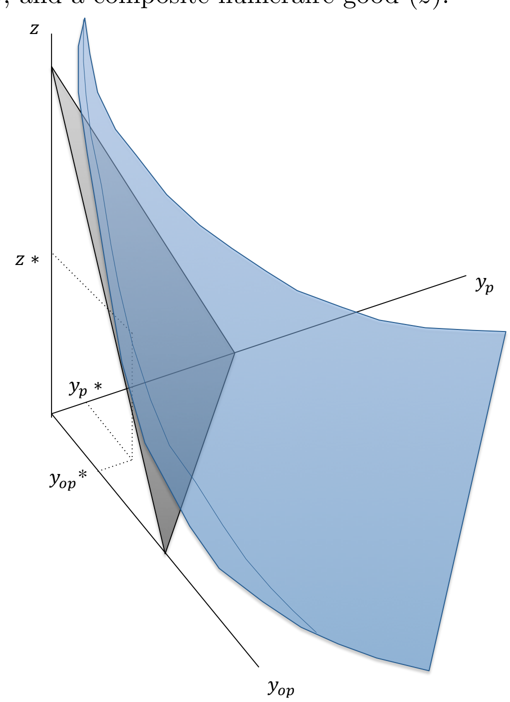
It is useful to think of this graphically. I suppress the i and m subscripts in this section for simplicity. First, to orient understanding, recall that in a standard non-reference-dependent case a consumer with income I, facing electricity prices $\boldsymbol{p} = (p_{op}, p_p)$ for electricity $\boldsymbol{y} = (y_{op}, y_p)$, and with a numeraire good z, would face the budget constraint defined by the plain in the top panel of Figure 1.2. This consumer would determine their level of peak and off-peak electricity consumption by maximizing their consumption utility subject to this budget constraint. The resulting optimal bundle is represented by (y_{op}^*, y_p^*, z^*) shown in the bottom panel of Figure 1.2.

[11] It is unclear whether all households received this "shadow" bill, or for how long, but if any feedback with regard to reference expenditure was given, it was in this form.

Figure 1.2: Three-Dimensional Standard Optimization Problem



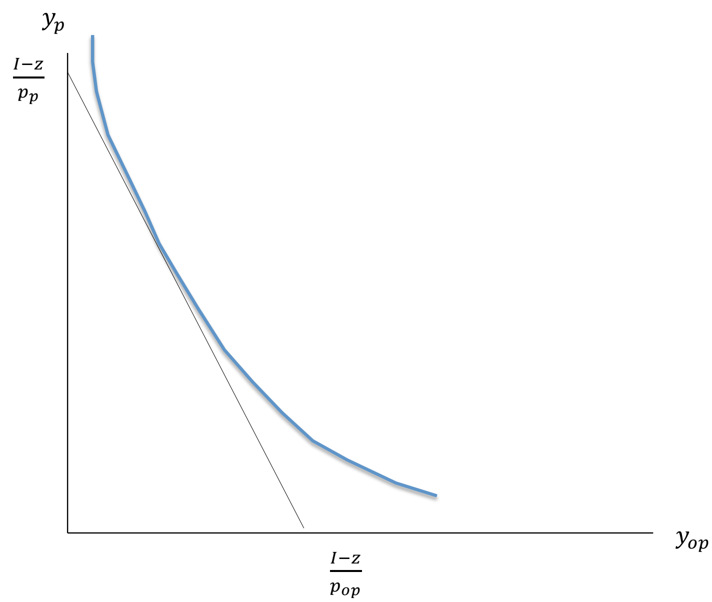
Note: The feasible set faced by a standard consumer demanding three goods: off-peak electricity (y_{op}), peak electricity (y_p), and a composite numeraire good (z).



Note: Three-dimensional representation of the standard non-reference-dependent optimization problem wherein the consumer maximizes their consumption utility (represented by the convex indifference surface) subject to the budget constraint plain.

Note that for a given level of z, we can project the standard non-reference-dependent optimization problem depicted in the bottom panel of Figure 1.2 as level sets of the budget constraint and utility function into two-dimensional (y_{op}, y_p) space, shown in Figure 1.3. I do this because we can more easily visualize loss aversion in two dimensions. Graphically the two-dimensional representation of the optimization problem for the loss-averse consumer who must maximize their kinked value function subject to their true budget constraint is represented in the top panel of Figure 1.4. The kink in the value function will be located where $\boldsymbol{y'} \cdot (\boldsymbol{p} - \boldsymbol{p}_r) = y_{op}(p_{op} - p_r) + y_p(p_p - p_r) = 0$. Solving for y_p, we see that in (y_{op}, y_p) space this is a line extending outward from the origin, with slope $\frac{(p_r - p_{op})}{(p_p - p_r)}$. This line is represented by the dotted line extending from the origin in Figure 1.4. Regardless of the level of income or consumption level of the numeraire good, the kink will always lie somewhere on this line.

Figure 1.3: Two-Dimensional Level Sets of Standard Optimization Problem



Note: Two-dimensional representation of the standard non-reference-dependent optimization problem projected into peak and off-peak electricity space (y_{op}, y_p) for a given level of the numeraire good (z) wherein the consumer maximizes their consumption utility (represented by the convex level-set) subject to the budget constraint line.

Now note that because I make the common assumptions of quasi-linear utility, constant marginal utility of income,[12] and risk neutrality over both losses and gains in expenditure, the model has the convenient feature that the kink in the value function characterizing loss aversion is only present in the linear portion of the quasi-linear value function. This is made explicit by rearranging the terms in Equation 1.2 to take the form in Equation 1.3.

$$
\begin{aligned}
U(\boldsymbol{y}_{im}; \boldsymbol{x}_{im}, p_{r,im}) =& u\left(\boldsymbol{y}_{im}; \boldsymbol{x}_{im}\right) \\
&+ \begin{cases} I_{im} - \boldsymbol{y}'_{im} \cdot \left[\boldsymbol{p}_{im} + \eta\lambda\left(\boldsymbol{p}_{im} - \boldsymbol{p}_{r,im}\right)\right] & \text{if } \boldsymbol{y}'_{im} \cdot \left(\boldsymbol{p}_{im} - \boldsymbol{p}_{r,im}\right) > 0 \\ I_{im} - \boldsymbol{y}'_{im} \cdot \left[\boldsymbol{p}_{im} + \eta\left(\boldsymbol{p}_{im} - \boldsymbol{p}_{r,im}\right)\right] & \text{if } \boldsymbol{y}'_{im} \cdot \left(\boldsymbol{p}_{im} - \boldsymbol{p}_{r,im}\right) \leq 0 \end{cases}
\end{aligned} \tag{1.3}
$$

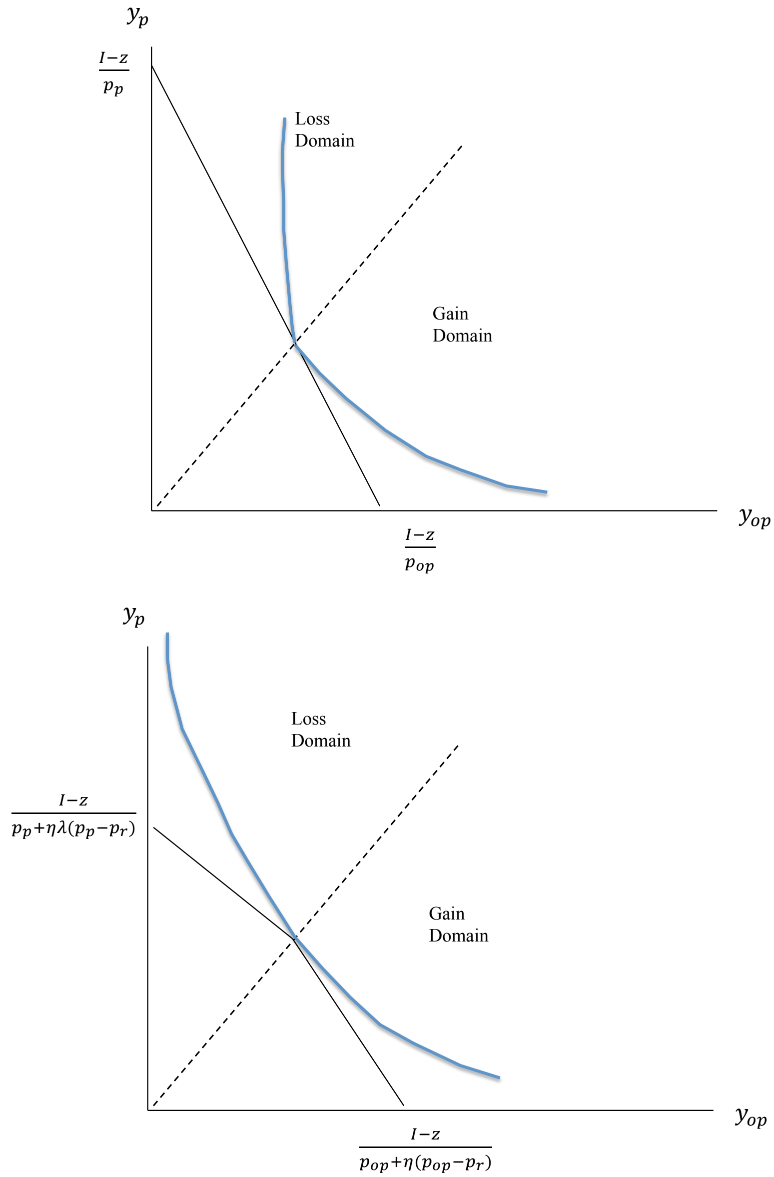
I can therefore transfer the kinked portion of the value function in the graphical representation into the linear portion of the optimization problem previously consisting solely of the budget constraint. This can be seen in the bottom panel of Figure 1.4. Pulling back and returning to a three-dimensional view of the problem, note that this kinked linear function in (y_{op}, y_p) space, shown in the bottom panel of Figure 1.4, is a projected level-set of a kinked plain in (y_{op}, y_p, z) space, shown in Figure 1.5. The loss-averse consumer will find their optimal level of peak, off-peak, and numeraire consumption by finding either the tangency between this kinked plain system and the indifference surface of their consumption utility, or the point at which the indifference surface touches the kink in the plain.

This allows for a unified way, shown in Equation 1.4, of representing the consumer's monthly value function for the two alternative models: the neoclassical model (no reference-dependence), and the reference-dependent model. In Equation 1.4, $\bar{\boldsymbol{p}}_{im}$ includes the reference-dependent kinked features of the value function. If the consumer either has no reference-dependent utility, or is a reference-dependent consumer on the standard (reference) pricing structure, then $\bar{\boldsymbol{p}}_{im}$ is simply their true prices, and the problem collapses to the standard problem represented in Figures 1.2 and 1.3. However, if the consumer has reference-dependent utility and is on the dynamic pricing structure, then $\bar{\boldsymbol{p}}_{im}$ is determined by their expenditure relative to their reference point. The object $\bar{\boldsymbol{p}}_{im}$ reflects the way that reference-dependent utility differentially affects the households' electricity consumption depending on their reference point and their degree of loss aversion. Note that $\bar{p}_{op} < p_{op}$, because it is assumed that $p_r > p_{op}$ whereas $\bar{p}_p > p_p$ as long as $p_r < p_p$. This determines the relative slopes of the legs of the kinked linear portion of the quasi-linear value function represented in the bottom panel of Figure 1.4.

$$
\begin{aligned}
U(\boldsymbol{y}_{im}; \boldsymbol{x}_{im}, p_{r,im}) &= u\left(\boldsymbol{y}_{im}; \boldsymbol{x}_{im}\right) + \left(I_{im} - \boldsymbol{y}'_{im} \cdot \bar{\boldsymbol{p}}_{im}\right) \\
&\text{where:} \\
\bar{\boldsymbol{p}}_{im} &= \boldsymbol{p}_{im} + \delta\left(\boldsymbol{p}_{im} - \boldsymbol{p}_{r,im}\right) \\
\delta &= \begin{cases} \eta\lambda & \text{if } \boldsymbol{y}'_{im} \cdot \left(\boldsymbol{p}_{im} - \boldsymbol{p}_{r,im}\right) > 0 \\ \eta & \text{if } \boldsymbol{y}'_{im} \cdot \left(\boldsymbol{p}_{im} - \boldsymbol{p}_{r,im}\right) \leq 0 \end{cases}
\end{aligned} \tag{1.4}
$$

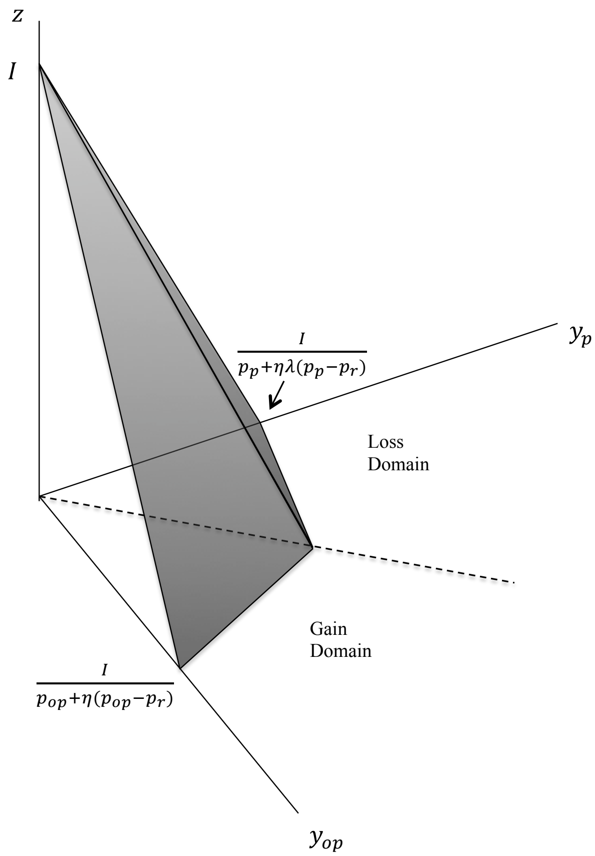
[12]Note that the assumption of constant marginal utility of income isn't unreasonable as the total expenditure on electricity is small relative to total income in general.

Figure 1.4: Two-Dimensional Level Sets of Loss Averse Optimization Problem



Note: Two-dimensional representation of the reference-dependent optimization problem projected into peak and off-peak electricity space (y_{op}, y_p) for a given level of the numeraire good (z). The dotted line extending from the origin represents the location of the kink in the value function for varying levels of income and consumption of the numeraire good. The top panel shows how the consumer maximizes their reference-dependent value function (represented by the kinked convex level-set) subject to the budget constraint line. In the bottom panel the kink in the reference-dependent portion of the utility has been incorporated into the budget constraint, creating a convex set represented by the kinked linear set here. The point of tangency (or point of contact at the kink) between the direct consumption utility (represented by the smooth indifference curve) and the kinked set for a given level of the numeraire good determines the optimum consumption bundle.

Figure 1.5: Three-Dimensional Kinked Set



Note: The three-dimensional representation of the combined budget constraint and kinked reference-dependent portion of the value function.

Characterizing the problem in this way results in a specification of the value function that is continuous and everywhere twice differentiable in $\bar{\boldsymbol{p}}_{im}$, therefore any standard utility specification can be used for the consumption utility over electricity, $u\left(\boldsymbol{y}_{im};\boldsymbol{x}_{im}\right)$. The value function is continuous everywhere in $\boldsymbol{y}_{im}$, but not differentiable in both arguments everywhere. The optimal bundle $\boldsymbol{y}^{*}_{im}$ each bill period is determined as described in Equation 1.5, and using the first order conditions shown in Equations 1.6 and 1.7. Finding the solution to this problem can be thought of as a two step process. First, the optimal bundle for each of two cases – on the kink or off the kink – would be determined. Call these two bundles $\boldsymbol{y}^{*off}_{im}$ and $\boldsymbol{y}^{*kink}_{im}$, respectively. Second, the value function would be evaluated at each bundle $U\left(\boldsymbol{y}^{*off}_{im};\boldsymbol{x}_{im},p_{r,im}\right)$ and $U\left(\boldsymbol{y}^{*kink}_{im};\boldsymbol{x}_{im},p_{r,im}\right)$, respectively. These two utility values would be compared, and the higher of the two would determined the ultimate optimal bundle consumed, $\boldsymbol{y}^{*}_{im}\left(\bar{\boldsymbol{p}}_{im}\right)$, shown in Equation 1.8.

$$\max_{\boldsymbol{y}_{im}} u\left(\boldsymbol{y}_{im};\boldsymbol{x}_{im}\right)+\left(I_{im}-\boldsymbol{y}'_{im}\cdot\bar{\boldsymbol{p}}_{im}\right) \tag{1.5}$$

First Order Conditions:

$$\text{If } \boldsymbol{y}'_{im}\cdot\left(\boldsymbol{p}_{im}-\boldsymbol{p}_{r,im}\right)\lesseqgtr 0: \tag{1.6}$$

$$\boldsymbol{y}^{*off}_{im} \text{ is the solution to: } \begin{cases} \frac{\partial u\left(\boldsymbol{y}^{*off}_{im};\boldsymbol{x}_{im}\right)}{\partial y_{op,im}}-\bar{p}_{op,im} & =0 \\ \frac{\partial u\left(\boldsymbol{y}^{*off}_{im};\boldsymbol{x}_{im}\right)}{\partial y_{p,im}}-\bar{p}_{p,im} & =0 \end{cases}$$

$$\text{If } \boldsymbol{y}'_{im}\cdot\left(\boldsymbol{p}_{im}-\boldsymbol{p}_{r,im}\right)=0: \tag{1.7}$$

$$\boldsymbol{y}^{*kink}_{im} \text{ is the solution to: } \begin{cases} \frac{\partial u\left(y^{*kink}_{op,im},\frac{\left(p_{r,im}-p_{op,im}\right)}{\left(p_{p,im}-p_{r,im}\right)}y^{*kink}_{op,im};\boldsymbol{x}_{im}\right)}{\partial y_{op,im}}-\frac{\left(p_{p,im}-p_{op,im}\right)p_{r,im}}{\left(p_{p,im}-p_{r,im}\right)} & =0 \\ y^{*kink}_{p,im}=\frac{\left(p_{r,im}-p_{op,im}\right)}{\left(p_{p,im}-p_{r,im}\right)}y^{*kink}_{op,im} \end{cases}$$

$$\boldsymbol{y}^{*}_{im}\left(\bar{\boldsymbol{p}}_{im}\right)=\begin{cases} \boldsymbol{y}^{*off}_{im} & \text{if } U\left(\boldsymbol{y}^{*off}_{im};\boldsymbol{x}_{im},p_{r,im}\right)>U\left(\boldsymbol{y}^{*kink}_{im};\boldsymbol{x}_{im},p_{r,im}\right) \\ \boldsymbol{y}^{*kink}_{im} & \text{if } U\left(\boldsymbol{y}^{*off}_{im};\boldsymbol{x}_{im},p_{r,im}\right)\leq U\left(\boldsymbol{y}^{*kink}_{im};\boldsymbol{x}_{im},p_{r,im}\right) \end{cases} \tag{1.8}$$

Additionally, any duality properties in this model hold in terms of $\bar{\boldsymbol{p}}_{im}$, but not in terms of true prices $\boldsymbol{p}_{im}$. In particular, the indirect value function, $V\left(\boldsymbol{I}_{im},\bar{\boldsymbol{p}}_{im};\boldsymbol{x}_{im}\right)$, will be such that Equation 1.9 holds. Moreover, Roy's Identity will hold anywhere off the kink with respect to $\bar{\boldsymbol{p}}_{im}$, but not with respect to $\boldsymbol{p}_{im}$.[13]

$$V\left(\boldsymbol{I}_{im},\bar{\boldsymbol{p}}_{im};\boldsymbol{x}_{im}\right)=U\left(\boldsymbol{y}^{*}_{im}\left(\bar{\boldsymbol{p}}_{im}\right);\boldsymbol{x}_{im},p_{r,im}\right) \tag{1.9}$$

where:

$$\boldsymbol{y}^{*}_{im}\left(\bar{\boldsymbol{p}}_{im}\right)=\begin{cases} \boldsymbol{y}^{*off}_{im} & \text{if } U\left(\boldsymbol{y}^{*off}_{im};\boldsymbol{x}_{im},p_{r,im}\right)>U\left(\boldsymbol{y}^{*kink}_{im};\boldsymbol{x}_{im},p_{r,im}\right) \\ \boldsymbol{y}^{*kink}_{im} & \text{if } U\left(\boldsymbol{y}^{*off}_{im};\boldsymbol{x}_{im},p_{r,im}\right)\leq U\left(\boldsymbol{y}^{*kink}_{im};\boldsymbol{x}_{im},p_{r,im}\right) \end{cases}$$

So now we have a model specifying the relationship between utility, reference-dependent utility, and demand in this setting. Ideally one would like to specify a reasonable functional form for $u\left(\boldsymbol{y}_{im};\boldsymbol{x}_{im}\right)$, derive the indirect value function and demand system on and off the kink, and directly estimate the parameters in the specified model. However, the problem with doing so is a familiar one for those who have dealt with kinked budget constraints. Any time the prices – played by $\bar{\boldsymbol{p}}_{im}$ in this model – are determined by the level of consumption, there is an endogeneity problem. One option would be to employ a structural approach based off of the classic work of Burtless and Moffitt (1984, 1985). This strategy I leave to future work. For now I will not estimate all the parameters in a structural model explicitly, but rather focus on showing evidence consistent with loss-aversion in a reduced-form way. The next two sections specify two sets of reduced form testable predictions that can be derived from this model.

[13]A proof of this is shown in Appendix A.3.

1.2.1 Testable Prediction 1: High probability of a loss leads to additional peak consumption reduction

The first testable prediction of the model has to do with consumption behavior off the kink. The model predicts that the more likely the consumer is to be in the loss domain with respect to monthly expenditure, the lower the peak consumption will be, and if peak and off-peak consumption are primarily substitutes, then the higher the off-peak consumption will be. To derive this prediction I bring our focus in to examine daily consumption behavior in this model, rather than monthly. The optimal level of monthly consumption previously modeled is made up of an aggregation of all the optimal amounts of daily consumption within the month. Equation 1.10 shows the daily optimization problem of consumer i on day t in month m, where month m has length M days. I introduce the assumption that the consumer is imperfect at predicting their consumption on future days, and potentially imperfect at recalling their consumption exactly for past days. Therefore, from the perspective of day t, assume $\boldsymbol{y}_{is} = \hat{\boldsymbol{y}}_{is} - \boldsymbol{e}_{is}$, $\forall s \neq t$, where $\hat{\boldsymbol{y}}_{is}$ is their predicted or recalled consumption on day $s \neq t$, $\boldsymbol{y}_{is}$ is there true observed consumption, and $\boldsymbol{e}_{is}$ is their prediction/recall error. Assume $\boldsymbol{e}_{is} = 0$ if $s = t$. Therefore, $\boldsymbol{loss}_{im} = \hat{\boldsymbol{loss}}_{im} - \boldsymbol{e}_{im}$, where $\boldsymbol{e}_{im} = \sum_{t=1}^{M} \boldsymbol{e}'_{it} \cdot \left(\boldsymbol{p}_{it} - \boldsymbol{p}_{r,it}\right)$, $\hat{\boldsymbol{loss}}_{im} = \sum_{t=1}^{M} \hat{\boldsymbol{y}}'_{it} \cdot \left(\boldsymbol{p}_{it} - \boldsymbol{p}_{r,it}\right)$ and $\boldsymbol{loss}_{im} = \sum_{t=1}^{M} \boldsymbol{y}'_{it} \cdot \left(\boldsymbol{p}_{it} - \boldsymbol{p}_{r,it}\right)$. The probability that the consumer i is in the loss domain for the month from the perspective of day t is $prob_{it}(\lambda) = prob_{it}(\boldsymbol{loss}_{im} > 0) = prob_{it}\left(\hat{\boldsymbol{loss}}_{im} > \boldsymbol{e}_{im}\right)$. Note that $p_{r,it}$ is not, as a rule, changing over the course of a month so the distinction between $p_{r,it}$ and $p_{r,im}$ is irrelevant from a practical perspective.

$$\max_{\boldsymbol{y}_{it}} U(\boldsymbol{y}_{it}; \boldsymbol{x}_{it}, p_{r,im}) = u(\boldsymbol{y}_{it}; \boldsymbol{x}_{it}) + (I_{it} - \boldsymbol{y}'_{it} \cdot \bar{\boldsymbol{p}}_{it}) \tag{1.10}$$

$$\begin{aligned} &\text{where:} \\ \bar{\boldsymbol{p}}_{it} &= \boldsymbol{p}_{it} + \Delta_{it}\left(\boldsymbol{p}_{it} - \boldsymbol{p}_{r,it}\right) \\ \Delta_{it} &= (1 - prob_{it}(\lambda)) \cdot \eta + prob_{it}(\lambda) \cdot \eta\lambda \\ prob_{it}(\lambda) &= prob_{it}(\boldsymbol{loss}_{im} > 0) \end{aligned}$$

It is useful at this point to provide a simple parameterized version the model. Assume the daily indirect value function for consumption off the kink takes the form presented in Equation 1.11.[14] The parameters of this model are $\alpha_{op}, \alpha_p, \beta_{op}, \beta_p, \gamma, \boldsymbol{\theta}_{op}$ and $\boldsymbol{\theta}_p$.

$$\begin{aligned} V_{it}(\bar{\boldsymbol{p}}_{it}, I_{it}; \boldsymbol{x}_{it}) =& I_{it} - \left(\alpha_{op} + \boldsymbol{\theta}'_{op} \cdot \boldsymbol{x}_{op,it}\right) \bar{p}_{op,it} - \left(\alpha_p + \boldsymbol{\theta}'_{op} \cdot \boldsymbol{x}_{op,it}\right) \bar{p}_{p,it} \\ & - \frac{\beta_{op}}{2} \bar{p}^2_{op,it} - \frac{\beta_p}{2} \bar{p}^2_{p,it} - \gamma \bar{p}_{op,it} \bar{p}_{p,it} \end{aligned} \tag{1.11}$$

Off the kink in this model, Roy's Identity holds with respect to $\bar{\boldsymbol{p}}_{im}$. We can therefore derive the demand equations for peak and off-peak electricity using the fact that

[14] I have derived the quadratic direct utility corresponding to this Gorman form of indirect utility. It is given in Appendix A.4.

$y^{*off}_{p,im} = -\frac{\partial V_{it}/\partial \bar{p}_{p,it}}{\partial V_{it}/\partial I_{it}}$ and $y^{*off}_{op,im} = -\frac{\partial V_{it}/\partial \bar{p}_{op,it}}{\partial V_{it}/\partial I_{it}}$. The resulting off-the-kink demand equations are presented in equations 1.12 and 1.13.

$$y^{*off}_{p,it}\left(\bar{\boldsymbol{p}}_{it};\boldsymbol{x}_{it}\right) = \alpha_p + \boldsymbol{\theta}'_p \cdot \boldsymbol{x}_{p,it} + \beta_p \bar{p}_{p,it} + \gamma \bar{p}_{op,it} \tag{1.12}$$
$$y^{*off}_{op,it}\left(\bar{\boldsymbol{p}}_{it};\boldsymbol{x}_{it}\right) = \alpha_{op} + \boldsymbol{\theta}'_{op} \cdot \boldsymbol{x}_{op,it} + \beta_{op} \bar{p}_{op,it} + \gamma \bar{p}_{p,it} \tag{1.13}$$

In Equations 1.14 and 1.15 I restate Equations 1.12 and 1.13 expanding $\bar{\boldsymbol{p}}_{it}$.

$$y^{*off}_{p,it}\left(\bar{\boldsymbol{p}}_{it};\boldsymbol{x}_{it}\right) = \alpha_p + \boldsymbol{\theta}'_p \cdot \boldsymbol{x}_{p,it} + \beta_p \left[p_{p,it} + \Delta_{it}\left(p_{p,it} - p_{r,it}\right)\right] + \gamma \left[p_{op,it} + \Delta_{it}\left(p_{op,it} - p_{r,it}\right)\right] \tag{1.14}$$
$$y^{*off}_{op,it}\left(\bar{\boldsymbol{p}}_{it};\boldsymbol{x}_{it}\right) = \alpha_{op} + \boldsymbol{\theta}'_{op} \cdot \boldsymbol{x}_{op,it} + \beta_{op} \left[p_{op,it} + \Delta_{it}\left(p_{op,it} - p_{r,it}\right)\right] + \gamma \left[p_{p,it} + \Delta_{it}\left(p_{p,it} - p_{r,it}\right)\right] \tag{1.15}$$

where:

$$\Delta_{it} = \left(1 - prob_{it}\left(\lambda\right)\right) \cdot \eta + prob_{it}\left(\lambda\right) \cdot \eta\lambda$$
$$prob_{it}\left(\lambda\right) = prob_{it}\left(\boldsymbol{loss}_{im} > 0\right)$$

The derivative of the off-the-kink demand equations with respect to $prob_{it}\left(\lambda\right)$ are shown in Equations 1.16 and 1.17. Assuming $\beta_p < 0$, $\beta_{op} < 0$, $\gamma > 0$, $\eta > 0$ and $\lambda > 1$, then $\frac{\partial y_{p,it}}{\partial prob_{it}(\lambda)} < 0$ and $\frac{\partial y_{p,it}}{\partial prob_{it}(\lambda)} > 0$.

$$\frac{\partial y_{p,it}}{\partial prob_{it}\left(\lambda\right)} = \left[\beta_p\left(p_p - p_r\right) + \gamma\left(p_{op} - p_r\right)\right]\left(\eta\lambda - \eta\right) \tag{1.16}$$

$$\frac{\partial y_{op,it}}{\partial prob_{it}\left(\lambda\right)} = \left[\beta_{op}\left(p_{op} - p_r\right) + \gamma\left(p_p - p_r\right)\right]\left(\eta\lambda - \eta\right) \tag{1.17}$$

Therefore, the model predicts that *ceteris paribus*, a loss averse consumer would consume less peak electricity on day t for a given level of peak prices if there is a higher probability they are in the loss domain relative to the gain domain for the month. Additionally, the model predicts that – particularly if peak and off-peak consumption are substitutes (i.e. $\gamma > 0$) – for a given level of prices a loss averse consumer will consume relatively more off-peak electricity if the probability of a loss is higher. Assuming there is an observable variable that is correlated with the probability of a monthly loss, but otherwise uncorrelated with consumption behavior on day t, the first testable prediction of the model is the following: if consumers are loss averse over monthly electricity expenditure, then the more likely it is that the consumer is in the loss domain with respect to monthly expenditure, the lower the peak consumption would be on regular peak and/or critical peak days, and the higher the off-peak consumption would be. If the consumer is not loss averse, then $\lambda = 1$, meaning there should be no correlation between the probability the consumer is in the loss domain, and the peak and off-peak daily consumption behavior because $\frac{\partial y_{p,it}}{\partial prob_{it}(\lambda)} = \frac{\partial y_{op,it}}{\partial prob_{it}(\lambda)} = 0$ in that case.

1.2.2 Testable Prediction 2: Clustering at the kink

The second testable prediction of the model is that if consumers are loss averse, then there is a disproportionate clustering of outcomes where $\left(p_{op} - p_r\right) y_{op} + \left(p_p - p_r\right) y_p = 0$, particularly when households are in regions of their consumption that place them close to the kink or would otherwise skew them slightly into the loss domain. This section outlines the intuition for why this is the case.

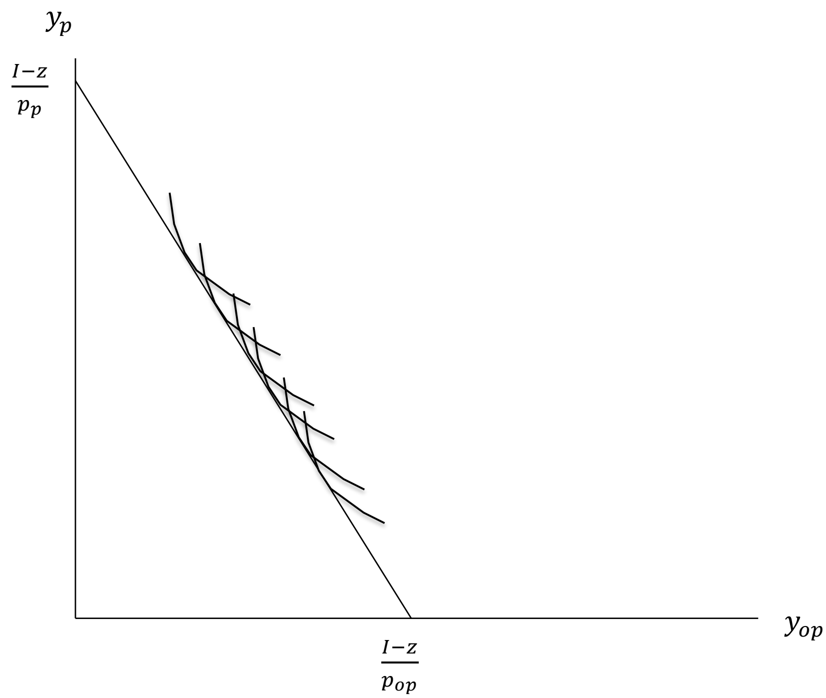
By collapsing the reference-dependent portion of the value function into the linear utility over the numeraire good, explicitly including the budget constraint as I have done above in Figure 1.4, and using the formulation in Equation 1.4, the problem begins to look very much like a standard utility maximization problem subject to a kinked budget constraint defined by $\bar{\boldsymbol{p}}$ and I. Previous work, particularly in the area of labor supply, has documented clustering of outcomes at the kink to be a feature of kinked constraints. Moffitt (1990) provides an excellent summary of this work, and discusses clustering at the kink in the budget constraint characterizing retirement age decisions found by Burtless and Moffitt (1984) and retirement consumption found by Burtless and Moffitt (1985). Another example with empirical evidence for this kind of bunching at kink points, here in the context of tax schedule kink points, is provided by Saez (2010).

To provide some intuition for how clustering at the kink relates to the model in this paper, consider the following thought experiment. Assume consumers are homothetic. Assume also that consumers are all identical other than being uniformly distributed with respect to the slope of the rays from the origin representing the expansion paths of the indifference curves relating to the direct consumption utility of these consumers. For consumers on the dynamic tariff with no reference-dependence, they would face the linear budget constraint given by the prices on their tariff. The nature of the heterogeneity described would mean that optimal bundles of (y_{op}, y_p) would be relatively evenly distributed across the budget constraint. This case is shown in Figure 1.6. If, however, these consumers had reference-dependent utility, and faced the kinked linear portion of their value function depicted in Figure 1.7, there would be clustering of (y_{op}, y_p) at the kink. In Figure 1.7, the solid indifference curves represent those consumers who are "caught on the kink" of the budget constraint.

The strength of the assumptions used to construct this example are not necessary to have this type of clustering. For example, a single consumer would have a distribution of (y_{op}, y_p) outcomes along their budget constraint because of various demand and price shocks over time. If this consumer tended to be near the kink in the budget constraint, there would be a disproportionate number of outcomes over time that would be clustered at the kink as well.

Therefore, this model predicts disproportionate clustering of (y_{op}, y_p) consumption where $(p_{op} - p_r)\, y_{op} + (p_p - p_r)\, y_p = 0$. Additionally, this clustering should be more pronounced if the relative prices are such that optimal outcomes are likely to be close to the kink and particularly if the consumer would otherwise be just skewed into the loss domain. If the kink is far away from where the indifference curves are tangent to the budget constraint, there is likely to be less clustering than if the kink is close to where the indifference curves are likely to hit the budget constraint. Also, if the prices are such that they would otherwise just be in the loss domain, their incentive – as we know from the first prediction of the model – is to cut back on expenditure, thereby pulling back towards the kink. This is not the case if they are just in the gain domain.

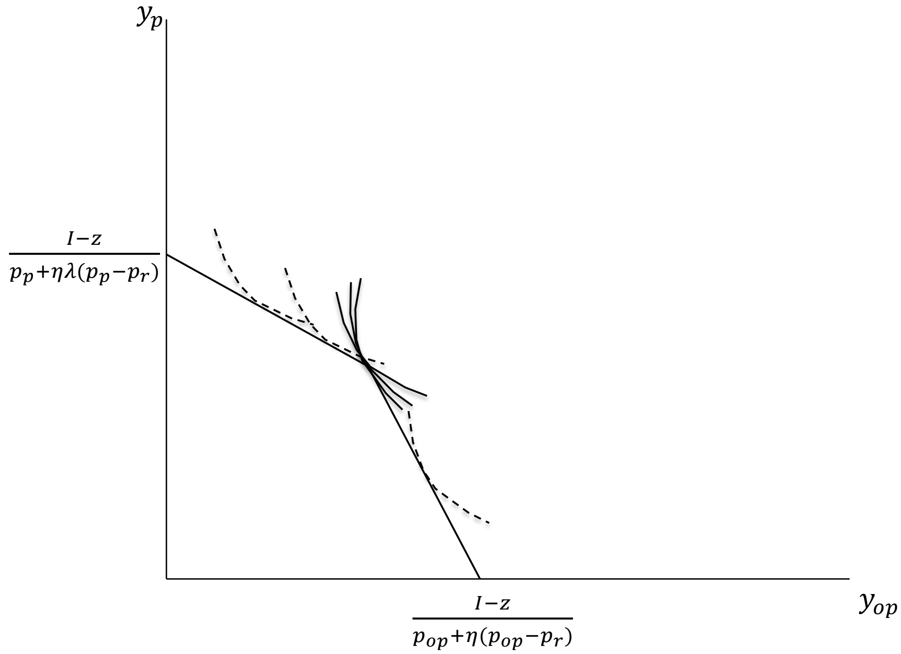
Figure 1.6: Even Distribution of Outcomes with No Kink



Note: None-reference-dependent case where all consumers have the same budget constraint, but there is a distribution of preferences across the population resulting in a relative even distribution of consumption outcomes across the budget constraint.

The prediction of a disproportionate clustering at the kink can be tested, as the location of the kink for varying levels of income and consumption of the numeraire good is a line from the origin with a positive slope determined solely by observable prices (shown as the dashed line in Figure 1.4). Therefore, the second testable prediction of this model is that, if consumers are loss averse over monthly expenditure on electricity, there is a disproportionate clustering of outcomes where $(p_{op} - p_r)\, y_{op} + (p_p - p_r)\, y_p = 0$, particularly when households are in regions of their consumption that place them close to the kink and otherwise would skew them into the loss domain.

Figure 1.7: Clustering at the Kink with Loss Aversion



Note: If the consumer has reference-dependent utility, then there will be a disproportionate number of consumption outcomes "caught on the kink" in the value function, shown here as the set of solid indifference curves.

1.3 Testing Model Predictions

In this section I present the strategies I use to test the two predictions motivated by the model. I first discuss testing for differential patterns of peak consumption depending on whether the consumer is more or less likely to be in the loss domain of their reference-dependent utility, then I go on to discuss clustering at the kink in the value function. Finally, I explore some alternative explanations for the patterns observed.

1.3.1 High Probability of a Loss Leads to Additional Peak Consumption Reduction

Recall the model predicts that the more likely it is the consumer is in the loss domain with respect to monthly expenditure, the more they will reduce their daily peak consumption and/or increase their daily off-peak consumption for given levels of peak and off-peak price. The intuition of the approach I take to test this prediction is that if a household has experienced a positive shock to their electricity expenditure in the early part of the month, thereby increasing the probability they will be in the loss domain for the month, the more strongly they will take measures to reduce their expenditure during the remainder of the month. In order to test this, I need an observable variable that is correlated with the probability of the household being in the loss domain for the month, but uncorrelated with electricity consumption on any given day. First, I determine which observable variables are correlated with the probability of a household experiencing a loss in a given bill period.

Using a linear probability model I regress the outcome of a loss or gain (an indicator variable equal to one in the case a household incurred a loss that bill period and zero otherwise) on the share of the bill period that is considered "summer" in terms of the pricing structure, the number of critical peak days called in a given bill period, the average number of degree-hours in the peak and off-peak periods, and household fixed effects.

As shown in Table 1.2, it is clear that the more critical peak days experienced in a given month, the more likely households would incur a loss that month; for each additional critical peak day experienced in a month, the probability that the average CPPH household will experience a loss is increased by 3.5 percentage points. The result for CPPL households is slightly stronger with the probability of experiencing a loss increasing by 7.73 percentage points. Additionally, the higher the number of degree-hours (a positive demand shock) in the high priced peak periods, the more likely the households will incur a loss. The magnitude for the degree-hour effect is on the order of an increase of one degree-hour experienced during peak hours on average resulting in an increase in the probability of experiencing a loss that bill period of 0.649 percentage points for CPPH households, and 0.532 percentage points for CPPL households. The standard deviation for the peak degree-hour measure is between 9 and 10 for all groups. Therefore, according to these results, an increase in average peak degree-hours of one standard deviation would increase the probability of a loss by about 6.4 percentage points for the CPPH group, and 5.3 percentage points for the CPPL group. Therefore, the effect of the degree-hour variable and the number of critical peak days variable have similar magnitudes of influence on the probability of a household experiencing a loss or gain in a given bill period.

As I mentioned, it is not enough that the observable variables identified be correlated with the probability the consumer is in the loss domain of their value function for the month. In order to dependably identify that there is indeed evidence of loss aversion, the variable must be correlated with the probability of a loss, but otherwise uncorrelated with the electricity consumption decision on a given observed day. I therefore define three identification strategies in the following way: first, I define a variable that is the number of critical peak days a household has experienced so far in a given bill period from the perspective of each day in the sample. To avoid the issue of mean reversion (which could potentially cause correlation between previous critical peak days called and current daily consumption), I limit the analysis to days at least one week after the previous critical peak day. Second, I again take advantage of the number of critical peak days, but instead of using the number of critical peak days called so far in a given bill period, I focus on the number of critical peak days a household experienced in the first week of the bill period. I then limit the analysis to the third week or more of the bill period to avoid the possibility that the number of critical peak days experienced in the first week of the bill period could influence the observed consumption decision of the household directly. Finally, I define the average level of peak degree-hours a household experiences in the first week of the bill period, and then again limit the analysis to the third week a beyond of the bill period.

Table 1.2: Linear Probability of Incurring a Monthly Loss

Dependent Variable: Loss (0,1)	(1) CPP High Ratio	(2) CPP Low Ratio
Critical Peak Days (Number in Bill Period)	0.0350***	0.0773***
	(0.00395)	(0.00460)
Summer Pricing (Share of Bill Period)	-0.798***	0.400***
	(0.0256)	(0.0268)
Peak Temperature	0.00649***	0.00532***
	(0.00209)	(0.00165)
Off-Peak Temperature	0.00291	-0.00856***
	(0.00181)	(0.00150)
Constant	0.680***	0.0288
	(0.0258)	(0.0250)
Household fixed effects	Y	Y
Observations (bill periods)	4,067	4,194
Total Number of Households	321	345
R-squared (within)	0.549	0.538

Standard errors clustered at household level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Results from linear probability model regressions with fixed effects. Shows the correlation between the monthly outcome of a household experiencing a loss or gain and a set of explanatory variables.

Therefore, the three independent variables of primary interest in this analysis are the number of critical peak days called so far in a bill period, the number of critical peak days called in the first week of a bill period, and the average peak degree-hour temperature measure in the first week of the bill period. In all three approaches I limit the analysis to the days in which peak hours are charged a peak prices (i.e. I eliminate weekends and holidays from the analysis). Additionally, to account for the possibility that the number of critical peak days may be otherwise correlated with electricity consumption,[15] I compare the consumption of households in the treatment group to the consumption of a control group that did not experience critical peak pricing. I use two different control groups, first I use the control group that was tracked for the original SPP pilot. These households had no knowledge that the pilot was taking place at all and faced standard non-dynamic prices throughout. Second, because the treatment groups selected into the experiment, thereby potentially making them systematically different from the control group in relevant ways, I also use the households who were placed on the TOU treatment as a comparison group. Additionally because, as can be seen in Figure 1.1, there is seasonal variation in prices that

[15] An example might be that early in the summer people haven't started using their air conditioning regularly, later in the summer they may have gotten around to programming their thermostat to come on regularly, or gotten more in the habit of using air conditioning; this creates positive correlation between electricity use and the number of critical peak day occurrences, as both are increasing over time, one by simple behavioral shift, the other by construction.

is less transparent to the consumer than the occurrence of critical peak days, I avoid the question of whether or not households are even aware of underlying seasonal price changes in the first place by controlling for the pricing phase of the pilot. This, in essence, controls for the level of prices as well, as they are more or less constant within a season/pricing phase, but does not try to identify a price response off of this seasonal price variation.

Results for this analysis, pooling both CPP treatment groups and using the control group as the counterfactual, are shown in Tables 1.3 and 1.4, and using the TOU households as the counterfactual are shown in Tables 1.5 and 1.6. TOU households did have slightly higher peak prices and slightly lower off-peak prices, but they did not experience critical peak days, nor were they aware that these days were occurring.

I use the estimating equation shown in Equation 1.18, motivated by Equation 1.12. In this equation i denotes a household; t denotes a day; $j \in \{op, p\}$ denotes either peak (p) or off-peak (op); y_{op} and y_p, measured in kWhs, are daily off-peak and peak electricity consumption respectively; D_{it} is one of the three conditioning variables of interest defined above (number of critical peak days called so far, number of critical peak days called in week one, or average peak degree-hours in week one of the bill period) for household i on day t, and $C_{it} \in \{0, 1\}$ is an indicator variable of whether or not day t was a critical peak day (for the control households the variable C_{it} is equal to one if their utility called a critical peak day that day, zero otherwise). Finally, $T_i \in \{0, 1\}$ is an indicator variable of whether or not household i is in one of the critical peak treatment groups. I control for peak and off-peak temperature measured in degree-hours separately for the peak and off-peak periods, month-of-year effects, day-of-weak effects, and whether day t for household i is in the summer or winter pricing phase (all captured in the vector of variables $\boldsymbol{x}_{j,it}$), as well as household fixed effects, γ_i. The parameters in the model are a_j, $\boldsymbol{d}_j$, and $b_{k,j}$, $k \in \{1, ..., 6\}$, $j \in \{op, p\}$.

$$\begin{aligned} y_{j,it} =& a_j + \boldsymbol{d}'_j \cdot \boldsymbol{x}_{j,it} + b_{1,j} C_{it} + b_{2,j} D_{it} + b_{3,j} D_{it} * C_{it} + b_{4,j} T_i * C_{it} \\ &+ b_{5,j} T_i * D_{it} + b_{6,j} T_i * D_{it} * C_{it} + \gamma_i + \varepsilon_{j,it} \\ &j \in \{op, p\} \end{aligned} \tag{1.18}$$

The parameters of primary interest are $b_{5,p}$, $b_{5,op}$, $b_{6,p}$ and $b_{6,op}$. Loss aversion would predict that $b_{5,p} < 0$ and/or $b_{6,p} < 0$ (note the p subscript), meaning that the higher the conditioning variable of interest (shown to be positively correlated with the probability the household is in the loss domain for the bill period), the less peak electricity the household will consume, either during normal peak hours and/or during critical peak hours. Loss aversion would also predict that $b_{5,op} > 0$ and/or $b_{6,op} > 0$ (note the op subscript, and that this prediction assumes peak and off-peak consumption are substitutes) because, if the consumer is in the loss domain not only is the own price effect magnified, but the cross price effect is as well.

Tables 1.3 and 1.4 present the results from three versions of regressions based on Equation 1.18 using the control group as the counterfactual. Table 1.3 presents the results of these regressions with peak consumption as the dependent variable, and Table 1.4 with off-peak consumption as the dependent variable, both of which use the control households as the counterfactual. In each case, the first and second columns are for the identification strategy using the number of critical peak days so far as the conditioning variable of interest; the third and fourth columns are for the identification strategy using the number of critical peak days in week one of the bill period as the conditioning variable of interest, and the fifth and sixth columns are for the identification strategy with average degree-hours in week one of the bill period as the conditioning variable of interest. Columns (1), (3) and (5) present the results from the full regressions based off of Equation 1.18 while Columns (2), (4) and (6) show results from each of the regressions restricting $b_{3,j} = 0$ and $b_{6,j} = 0$. The regressions in Columns (2), (4) and (6) are the preferred specifications. This is discussed in more detail below.

Looking broadly at Tables 1.3 and 1.4 – particularly Columns (2), (4) and (6) – the results generally comply with intuition. Households consume more peak electricity when peak degree-hours are higher, similarly for off-peak electricity and off-peak degree-hours. Households consume more peak and off-peak electricity on critical peak days (hence the reason the critical peak day was called in the first place), but treatment households respond to the higher critical peak prices and consume less (by 1.1 to 1.4 kWh relative to control households, which is about 20% of average daily peak electricity consumption) than control households on critical peak days. Interestingly households do not seem to consume more peak electricity on average in the summer pricing phases relative to the winter, but do seem to consume less off-peak electricity in the summer relative to the winter. This may have to do with differences in heating and cooling behavior. Perhaps electric heating systems are kept on more systematically in the winter than air conditioning systems are in the summer, the usage of which may be more peaky.

To look closely at the results regarding loss aversion. The null hypothesis of this analysis is that fluctuation in any of the three conditioning variables of interest is uncorrelated with the electricity consumption choice (i.e. that $b_{5,p} = 0$ and $b_{6,p} = 0$). As you can see, the null hypothesis that $b_{5,p} = 0$ can be rejected. Results for $b_{6,p} = 0$, while negative in all cases, are less consistent. However, I am suspicious of the specifications including $D*C$ and $T*D*C$. In the Column (5) results in Table 1.3 this is in part because the number of degree-hours in the first week of the bill period are highly correlated with whether a given day is a critical peak day. Additionally the coefficient on $T*C$ is not statistically significant in Column (5) of Table 1.3, but is statistically significant on that variable in all other specifications. It is expected that the coefficient on $T*C$ be negative and significant, as this is the variable that identifies the price impact of critical peak days relative to regular peak price days for the treatment groups relative to the control group. I believe that the variables $D*C$ and $T*D*C$ are absorbing the $T*C$ and C effects to some extent. Therefore the most accurate analysis in all cases are those which restrict the coefficients on $D*C$ and $T*D*C$ to be equal to zero. This explicitly assumes that the impact of previous positive shocks to expenditure on subsequent peak consumption are similar regardless of whether the subsequent day is a critical peak day or a regular peak day. This choice is justified for the following reasons. When this restriction is imposed, the coefficients on C and $T*C$ become consistent with all other specifications. Moreover, in all specifications in which this confounding effect is not as prominent, the coefficients on $D*C$ and $T*D*C$ are not significant.

Table 1.3: Peak kWh: CPP vs Control

Dependent Variable: Peak kWh						
	(1)	(2)	(3)	(4)	(5)	(6)
T=1: CPP T=0: Control	D = Number of critical peak days so far		D = Number of critical peak days in week 1		D = Peak temperature in week 1	
C ($b_{1,p}$)	0.673***	1.027***	0.525***	0.597***	-0.731***	0.571***
	(0.175)	(0.141)	(0.135)	(0.117)	(0.155)	(0.0990)
D ($b_{2,p}$)	0.00956	0.0512*	0.0465	0.0584	0.0893***	0.0991***
	(0.0288)	(0.0286)	(0.0627)	(0.0658)	(0.0123)	(0.0128)
D * C ($b_{3,p}$)	0.191***		0.109		0.0832***	
	(0.0717)		(0.0978)		(0.0100)	
T * C ($b_{4,p}$)	-1.204***	-1.438***	-1.168***	-1.296***	-0.244	-1.121***
	(0.219)	(0.191)	(0.193)	(0.173)	(0.199)	(0.141)
T * D ($b_{5,p}$)	-0.0668*	-0.0914***	-0.213***	-0.236***	-0.0596***	-0.0661***
	(0.0345)	(0.0345)	(0.0706)	(0.0729)	(0.0161)	(0.0168)
T * D * C ($b_{6,p}$)	-0.123		-0.202		-0.0560***	
	(0.0868)		(0.124)		(0.0138)	
Summer Pricing	-0.0907	-0.0896	0.118	0.118	0.0893	0.0993
	(0.0743)	(0.0743)	(0.0833)	(0.0833)	(0.0842)	(0.0847)
Peak Degree Hours	0.172***	0.172***	0.191***	0.191***	0.172***	0.174***
	(0.00748)	(0.00748)	(0.00803)	(0.00803)	(0.00690)	(0.00700)
Constant	4.264***	4.235***	3.955***	3.956***	3.554***	3.411***
	(0.121)	(0.120)	(0.142)	(0.141)	(0.171)	(0.174)
Day-of-week effects	Y	Y	Y	Y	Y	Y
Month-of-year effects	Y	Y	Y	Y	Y	Y
Household fixed effects	Y	Y	Y	Y	Y	Y
Daily Observations	191,839	191,839	149,344	149,344	149,344	149,344
R-squared (within)	0.164	0.164	0.18	0.180	0.19	0.188
Average Peak kWh/day	5.45	5.45	5.4	5.4	5.4	5.4
Num. of Households (T=1)	666	666	655	655	655	655
Num. of Households (T=0)	418	418	416	416	416	416
Total Number of Households	1,084	1,084	1,071	1071	1,071	1,071

Standard errors clustered at household level in parentheses

*** p<0.01, ** p<0.05, *p<0.1

Note: Results of fixed-effect regressions exploring the correlation of daily peak kWh usage during a subsample of days in the experiment and a set of explanatory variables. The CPPL and CPPH treatment groups are pooled and the control group is used as the counterfactual. Eight CPPH, three CPPL, and two control households who appeared in the Columns (1) & (2) regressions are dropped from the regressions presented in Columns (3) through (6). These households appear in the regression presented in Columns (1) & (2) because they have observations at least a week after the previous critical peak pricing day, but are dropped from the other regressions because they have no observations in the third and fourth week of the bill period. A total of only 92 (0.06%) daily observations are dropped due to the exclusion of these thirteen households.

I restrict my discussion of the specific results to the preferred specifications (Columns (2), (4) and (6)). I turn first to Table 1.3: consistently, consumers reduce their regular peak consumption more relative to the control group if any one of the three variables of interest are increased. This is consistent with the model of loss aversion. In particular, focusing first on Column (2), an increase in the number of critical peak days experienced so far in a bill period decreases the amount of regular peak electricity the household consumes subsequently in the bill period by 0.0914 kWhs per day (1.69% of average daily peak electricity consumption) for the CPP treatment groups relative to the control group. In Column (4), it can be seen that a one day increase in the number of critical peak days experienced in the first week of the bill period resulted in a decrease in the peak electricity consumed on average in the last weeks of the bill period by 0.236 kWhs per day (4.37%) for the CPP treatment groups relative to the control group. Finally, looking at Column 6, an increase of one degree-day on average in the first week of the bill period resulted in a decrease in peak electricity consumption in the last weeks of the bill period of 0.0661 kWhs per day on average (1.22%) for the CPP treatment group relative to the control group.

I conclude from these results that an increase in any of these three shocks to the probability that the household is in the loss domain (i.e. the number of critical peak days experienced so far, the number of critical peak days experienced in the first week of the bill period, and the average peak degree-hours in the first week of the bill period) resulted in a statistically significant decrease in subsequent peak electricity consumption for treated households relative to control households. However, this result does not consistently appear to differ between regular and critical peak days.

Now I discuss the results from Table 1.4, wherein the results from regressions testing the null hypotheses that $b_{5,op} = 0$ and $b_{6,op} = 0$ are presented. The results for these tests are inconclusive. The coefficients $b_{5,op}$ and $b_{6,op}$ are not statistically significantly different from zero in any of the specifications, and the signs for these two effects change across the three types of regressions. This is neither in support of, nor inconsistent with, loss aversion. If there is no cross-elasticity between peak price and off-peak consumption, which is suggested by the changing sign and inconsistent results of the coefficient on $T * C$ in Table 1.4, then multiplying an imprecise zero by a constant will result in an imprecise zero, as we see here.

Table 1.4: Off-Peak kWh: CPP vs Control

Dependent Variable: Off-Peak kWh						
	(1)	(2)	(3)	(4)	(5)	(6)
T=1: CPP T=0: Control	D = Number of critical peak days so far		D = Number of critical peak days in week 1		D = Peak temperature in week 1	
C ($b_{1,p}$)	1.051***	1.773***	0.594***	0.932***	-1.229***	0.963***
	(0.275)	(0.206)	(0.206)	(0.180)	(0.233)	(0.150)
D ($b_{2,p}$)	-0.0682	0.0248	-0.145	-0.0809	0.175***	0.194***
	(0.0597)	(0.0522)	(0.118)	(0.122)	(0.0227)	(0.0234)
D * C ($b_{3,p}$)	0.386***		0.492***		0.139***	
	(0.122)		(0.145)		(0.0159)	
T * C ($b_{4,p}$)	-0.647*	-0.291	0.268	0.0827	0.197	0.195
	(0.374)	(0.300)	(0.321)	(0.288)	(0.349)	(0.231)
T * D ($b_{5,p}$)	0.0243	0.0687	0.0329	0.00494	-0.0329	-0.0348
	(0.0756)	(0.0682)	(0.143)	(0.147)	(0.0285)	(0.0297)
T * D * C ($b_{6,p}$)	0.225		-0.254		0.00141	
	(0.161)		(0.196)		(0.0238)	
Summer Pricing	-0.443***	-0.438***	-0.369**	-0.369**	-0.281	-0.267
	(0.155)	(0.155)	(0.169)	(0.169)	(0.173)	(0.173)
Off-Peak Degree Hours	0.318***	0.320***	0.392***	0.392***	0.344***	0.354***
	(0.0207)	(0.0206)	(0.0246)	(0.0246)	(0.0221)	(0.0222)
Constant	16.86***	16.75***	16.82***	16.79***	14.80***	14.45***
	(0.266)	(0.264)	(0.287)	(0.287)	(0.322)	(0.324)
Day-of-week effects	Y	Y	Y	Y	Y	Y
Month-of-year effects	Y	Y	Y	Y	Y	Y
Household fixed effects	Y	Y	Y	Y	Y	Y
Daily Observations	191,839	191,839	149,344	149,344	149,344	149,344
R-squared (within)	0.106	0.105	0.124	0.124	0.146	0.143
Average Peak kWh/day	16.34	16.34	16.27	16.27	16.27	16.27
Num. of Households (T=1)	666	666	655	655	655	655
Num. of Households (T=0)	418	418	416	416	416	416
Total Number of Households	1,084	1,084	1,071	1,071	1,071	1,071

Standard errors clustered at household level in parentheses
*** p<0.01, ** p<0.05, *p<0.1

Note: Results of fixed-effect regressions exploring the correlation of daily off-peak kWh usage during a subsample of days in the experiment and a set of explanatory variables. The CPPL and CPPH treatment groups are pooled and the control group is used as the counterfactual. Eight CPPH, three CPPL, and two control households who appeared in the Columns (1) & (2) regressions are dropped from the regressions presented in Columns (3) through (6). These households appear in the regression presented in Columns (1) & (2) because they have observations at least a week after the previous critical peak pricing day, but are dropped from the other regressions because they have no observations in the third and fourth week of the bill period. A total of only 92 (0.06%) daily observations are dropped due to the exclusion of these thirteen households.

I run the same set of regressions using the TOU treatment group as the counterfactual group, once again to account for the fact that the treatment households selected into treatment. Results for these regressions can be seen in Tables 1.5 and 1.6. Looking first at the results for the peak electricity consumption in Table 1.5 and once again restricting my discussion to the preferred specifications presented in Columns (2), (4) and (6), the sign of $b_{5,p}$ is negative for all identification strategies. However, interestingly, the $b_{5,p}$ coefficient is only statistically significantly different from zero in the two regressions using measures of previous critical peak days experienced. The results indicate that an increase in the previous number of critical peak days experienced so far in the bill period was associated with a reduction of 0.0851 kWh of peak consumption during subsequent peak hours relative to TOU households. This is 1.58% of average peak consumption. Additionally, an increase the number of critical peak days experienced in the first week of the bill period was associated with a reduction of 0.17 kWh (3.15% of average daily peak consumption) of peak electricity consumption relative to the TOU group.

When measures of previous critical peak days are used to identify shocks to the probability of a loss the $b_{5,p}$ coefficient is significant when both the TOU and control households are used as counterfactuals. On the other hand when shocks to the probability of a loss are in the form of higher peak temperatures, the $b_{5,p}$ coefficient is significant only for the case with the control group as the counterfactual, and not the TOU counterfactual. This difference makes sense; the TOU group is also on an experimental pricing structure wherein higher prices are charged in peak hours and lower prices charged in off-peak hours. Therefore, shocks in the form of more critical peak days called would not increase the probability of a TOU household incurring a loss, because TOU households don't experience critical peak days, but higher peak temperatures would increase the probability of a TOU household incurring a loss. Therefore, higher peak temperatures in the first week of a TOU household's bill period might also induce them to cut back disproportionately on peak consumption later in the bill period in order to avoid their own loss. This additional cut back would make sense for the TOU group, but not for the control group. Hence, the difference in behavior of the CPP groups relative to each one of these groups when shocks to the probability of a loss are from higher temperatures would be expected to be more significant for the control counterfactual than the TOU counterfactual.

Similar to the case using the control group as the counterfactual, when the TOU households were used as the counterfactual, the results when looking at the off-peak consumption patterns were inconclusive with no statistically significant results for $b_{5,op}$ and $b_{6,op}$, as well as inconsistent signs. These results are shown in Table 1.6.

The analysis demonstrates evidence that when there is a higher probability a household is in the loss domain due to previous shocks to monthly expenditure in the form of higher previous peak degree-hours, or more previous critical peak days, the more households cut back on subsequent peak consumption.[16]

[16]Two different robustness checks were run omitting different subsets of the data. The results for these robustness checks are presented in Appendix A.2, along with an explanation of why those checks were run. In all cases the results remain significant in the same pattern as they do in the primary regressions.

Table 1.5: Peak kWh: CPP vs TOU

Dependent Variable: Peak kWh						
	(1)	(2)	(3)	(4)	(5)	(6)
T=1: CPP T=0: TOU	D = Number of critical peak days so far		D = Number of critical peak days in week 1		D = Peak temperature in week 1	
C ($b_{1,p}$)	-0.0737	0.442***	0.252	0.300*	-0.952***	0.363***
	(0.167)	(0.152)	(0.168)	(0.155)	(0.161)	(0.131)
D ($b_{2,p}$)	0.00671	0.0704**	0.0595	0.0662	0.0636***	0.0745***
	(0.0326)	(0.0354)	(0.0750)	(0.0797)	(0.0144)	(0.0153)
D * C ($b_{3,p}$)	0.288***		0.0758		0.0894***	
	(0.0920)		(0.113)		(0.0133)	
T * C ($b_{4,p}$)	-0.303	-0.690***	-0.669***	-0.789***	0.0754	-0.777***
	(0.204)	(0.191)	(0.210)	(0.196)	(0.200)	(0.163)
T * D ($b_{5,p}$)	-0.0397	-0.0851**	-0.149*	-0.170**	-0.0220	-0.0294
	(0.0377)	(0.0412)	(0.0817)	(0.0863)	(0.0180)	(0.0190)
T * D * C ($b_{6,p}$)	-0.216**		-0.194		-0.0597***	
	(0.104)		(0.136)		(0.0163)	
Summer Pricing	-0.0922	-0.0894	0.0711	0.0706	0.0209	0.0308
	(0.0768)	(0.0768)	(0.0848)	(0.0848)	(0.0854)	(0.0857)
Peak Degree Hours	0.155***	0.155***	0.170***	0.170***	0.153***	0.155***
	(0.00784)	(0.00783)	(0.00839)	(0.00838)	(0.00720)	(0.00729)
Constant	4.029***	3.996***	3.750***	3.758***	3.429***	3.302***
	(0.129)	(0.128)	(0.148)	(0.148)	(0.179)	(0.183)
Day-of-week effects	Y	Y	Y	Y	Y	Y
Month-of-year effects	Y	Y	Y	Y	Y	Y
Household fixed effects	Y	Y	Y	Y	Y	Y
Daily Observations	159,244	159,244	123,564	123,564	123,564	123,564
R-squared (within)	0.143	0.143	0.159	0.159	0.166	0.165
Average Peak kWh/day	5.12	5.12	5.1	5.1	5.1	5.1
Num. of Households (T=1)	666	666	655	655	655	655
Num. of Households (T=0)	240	240	237	237	237	237
Total Number of Households	906	906	892	892	892	892

Standard errors clustered at household level in parentheses

*** p<0.01, ** p<0.05, *p<0.1

Note: Results of fixed-effect regressions exploring the correlation of daily peak kWh usage during a subsample of days in the experiment and a set of explanatory variables. The CPPL and CPPH treatment groups are pooled and the TOU group is used as the counterfactual. Eight CPPH, three CPPL, and two TOU households who appeared in the Columns (1) & (2) regressions are dropped from the regressions presented in Columns (3) through (6). These households appear in the regression presented in Columns (1) & (2) because they have observations at least a week after the previous critical peak pricing day, but are dropped from the other regressions because they have no observations in the third and fourth week of the bill period. A total of only 92 (0.07%) daily observations are dropped due to the exclusion of these thirteen households.

Table 1.6: Off-Peak kWh: CPP vs TOU

Dependent Variable: Off-Peak kWh						
	(1)	(2)	(3)	(4)	(5)	(6)
T=1: CPP T=0: TOU	D = Number of critical peak days so far		D = Number of critical peak days in week 1		D = Peak temperature in week 1	
C ($b_{1,p}$)	0.480	1.408***	0.459	0.813***	-1.259***	0.955***
	(0.329)	(0.288)	(0.304)	(0.276)	(0.347)	(0.239)
D ($b_{2,p}$)	-0.0453	0.0786	-0.0931	-0.0255	0.153***	0.173***
	(0.0719)	(0.0685)	(0.138)	(0.143)	(0.0273)	(0.0293)
D * C ($b_{3,p}$)	0.513***		0.528**		0.150***	
	(0.175)		(0.221)		(0.0267)	
T * C ($b_{4,p}$)	0.00195	0.158	0.512	0.305	0.177	0.239
	(0.408)	(0.362)	(0.384)	(0.354)	(0.444)	(0.301)
T * D ($b_{5,p}$)	-0.0145	0.000740	-0.0242	-0.0582	-0.0160	-0.0193
	(0.0844)	(0.0801)	(0.158)	(0.164)	(0.0321)	(0.0343)
T * D * C ($b_{6,p}$)	0.101		-0.299		-0.00309	
	(0.205)		(0.260)		(0.0326)	
Summer Pricing	-0.486***	-0.478***	-0.413**	-0.414**	-0.391**	-0.375**
	(0.157)	(0.157)	(0.172)	(0.171)	(0.175)	(0.176)
Off-Peak Degree Hours	0.297***	0.300***	0.365***	0.365***	0.320***	0.329***
	(0.0219)	(0.0219)	(0.0255)	(0.0255)	(0.0224)	(0.0227)
Constant	16.77***	16.65***	16.81***	16.78***	15.06***	14.71***
	(0.280)	(0.276)	(0.301)	(0.302)	(0.348)	(0.353)
Day-of-week effects	Y	Y	Y	Y	Y	Y
Month-of-year effects	Y	Y	Y	Y	Y	Y
Household fixed effects	Y	Y	Y	Y	Y	Y
Daily Observations	159,244	159,244	123,564	123,564	123,564	123,564
R-squared (within)	0.096	0.096	0.115	0.114	0.134	0.131
Average Peak kWh/day	16.38	16.38	16.27	16.27	16.27	16.27
Num. of Households (T=1)	666	666	655	655	655	655
Num. of Households (T=0)	240	240	237	237	237	237
Total Number of Households	906	906	892	892	892	892

Standard errors clustered at household level in parentheses
*** p<0.01, ** p<0.05, *p<0.1

Note: Results of fixed-effect regressions exploring the correlation of daily off-peak kWh usage during a subsample of days in the experiment and a set of explanatory variables. The CPPL and CPPH treatment groups are pooled and the TOU group is used as the counterfactual. Eight CPPH, three CPPL, and two TOU households who appeared in the Columns (1) & (2) regressions are dropped from the regressions presented in Columns (3) through (6). These households appear in the regression presented in Columns (1) & (2) because they have observations at least a week after the previous critical peak pricing day, but are dropped from the other regressions because they have no observations in the third and fourth week of the bill period. A total of only 92 (0.07%) daily observations are dropped due to the exclusion of these thirteen households.

1.3.2 Clustering at the Kink

I now turn to the second testable prediction of the model. Recall that Section 1.2.2 outlined the model prediction that a disproportionate number of outcomes should occur at the kink in the value function, particularly when prices are such that households tend to be otherwise located close to the kink and skewed into the loss domain. In this section I first characterize when households in this pilot are likely to be close to the kink and/or skewed into the loss domain. Second, I determine the degree of clustering during these periods relative to periods when they are likely to be further from the kink.

Note that there are two main sources of price variation in this pilot. First, there is cross-sectional variation, as prices differ between the CPPH and CPPL treatment groups. Second, within each treatment there is time-series variation, as the summer and winter prices differ for both groups. The question is, during which pricing phase will each group be more likely to be consuming close to the kink and/or skewed into the loss domain?

Recall that the kink is located where $(p_{op,im} - p_{r,im})\, y_{op,im} + (p_{p,im} - p_{r,im})\, y_{p,im} = 0$. I make the assumption that the location of the kink is known to the households with some error, and so I allow for clustering to be within close proximity of the kink. To that end I define the range of net expenditure outcomes to be located "at the kink" if they are within \$6 of the kink, which is approximately 6.8% of average total monthly bill paid by CPP treatment group participants in the experiment. In order to determine which pricing phases for each treatment group are more likely to result in outcomes close to the kink (and therefore more likely to be "caught on the kink"), I calculate the share of outcomes in each pricing phase for each treatment group that are within \$12 of the kink.[17] This is simply a doubling of the range defined as "on the kink." When I make this calculation I obtain the values presented in Table 1.7. We see that for the CPPH treatment, 65% are within \$12 of the kink during the summer pricing phase, and 91% of outcomes are within \$12 of the kink in the winter pricing phase. Conversely, for the CPPL treatment, 88% are within \$12 of the kink in the summer pricing phase, while only 85% are within \$12 of the kink in the winter pricing phase. While the CPPL treatment experienced less of a difference in the likelihood of being close to the kink between the two pricing phases, we see that the pricing phases that result in a higher likelihood of being near the kink are winter for the CPPH treatment, and summer for the CPPL treatment. According to the prediction of the model then, the times we should expect to see the most clustering are the winter pricing phase for the CPPH group, and summer for the CPPL group.

Even more compelling is that the CPPH treatment was designed such that households should be in the gain domain in the summer and be in the loss domain in the winter.

[17] The choice of \$6 as the range around zero to define as "on the kink" is somewhat arbitrary. The logic came from the histograms in Figures 1.8 and 1.9 themselves. A bar width within the histograms of \$4 was chosen as a reasonable width to demonstrate the distribution given the variability in the net expenditure in the data. Once that bar width was established, I wanted the "on the kink" range surrounding the kink to correspond to the visualization provided by the histograms, and \$2 (focusing only on the bar centered at zero) seemed to be too precise a measure to reasonably assume households could target given the complexity of controlling electricity usage. I therefore added one additional bar on either side of zero to the range defined as the kink, resulting in a range of \$6 around the kink. Then, expanding this range to determine the share of households "close to the kink" (i.e. \$12) I chose to simply double the range on either side of zero previously defined as "on the kink."

Conversely the CPPL treatment rates were designed so that they should be in the gain domain in the winter and the loss domain in the summer (CRA, 2005). The model predicts that we are more likely to see clustering in the season, not only when they are close to the kink, but also when they might otherwise have been skewed into the loss domain. If the rate structure is such that they will gain, there is no incentive to shift expenditure towards the kink, but if the rate structure is such that they would likely otherwise lose, there is, as we've shown, more incentive to pull expenditure back to, and therefore cluster at, the kink. Indeed, this is the pattern seen below. I now discuss in detail how I measure clustering.

Table 1.7: Probability of Being Close to the Kink

	CPPH Summer	CPPH Winter	CPPL Summer	CPPL Winter
Share of outcomes within $12 of the kink	0.6617	**0.9117**	**0.8899**	0.8447

Note: The probability of being close to the kink in each of the pricing phases for the two treatment groups of interest. These probabilities are calculated by dividing the number of net expenditure outcomes within $12 of zero by the total number of observations, in each season for each treatment group.

To demonstrate clustering at the kink I could simply show a histogram of net expenditure outcomes (i.e. $(p_{op,im} - p_{r,im})\, y_{op,im} + (p_{p,im} - p_{r,im})\, y_{p,im}$), which do indeed show a large spike right around zero. However, the treatment prices were constructed in such a way as to explicitly avoid large losses.[18] Therefore one might expect to see clustering around zero simply by construction of the treatment tariffs themselves, and not because of household behavior. Because of this I ascertain whether the degree of clustering at the kink is disproportionately due to household reference-dependent behavior while on the treatment price structures, rather than simply coincidental. To this end, I construct what I refer to as a counterfactual expenditure by determining what control households would have spent given treatment prices relative to what they actually spent given control prices. I then plot the histogram of this control net expenditure overlying that of the treatment households. Theoretically, the difference in these two distributions should reflect actual behavioral change instigated by the treatment prices.

I do the same thing using the TOU households as the counterfactual and calculate the cost of TOU consumption at the CPPL and CPPH treatment prices, respectively. As mentioned, using the TOU treatment groups as the counterfactual for the CPP treatment groups, rather than using the control group, does help to account for selection. This is particularly important for testing the degree of clustering. This is because it is expected that households that consume less peak electricity on average are likely to have selected into the treatment groups, and therefore the treatment households, CPP and TOU alike, are likely to be less "peaky" in their consumption patterns than the control households. This may mean that they are simply more likely to be located close to the kink in general, relative to the control

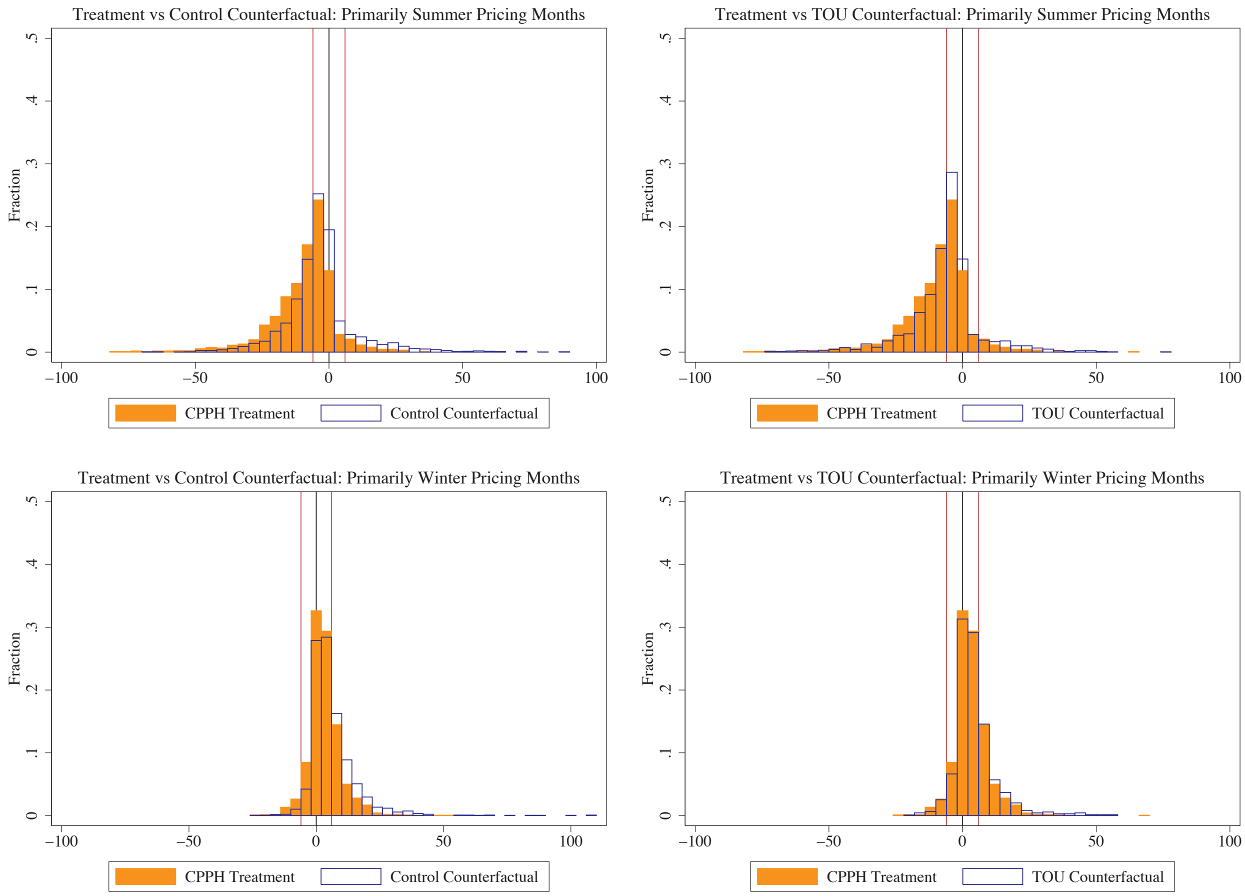
[18]The experimental rates had to meet three requirements: by revenue-neutral for the average customer over the year assuming unchanged load shape, not change the bills by more than 5% assuming unchanged load shape, and provide customers with the opportunity to save 10% on their bills if they reduced peak consumption by 30% (CRA, 2005).

households. However, there are problems with using the TOU treatment groups as the counterfactual as well, as they tend to disproportionately be customers of PG&E, and not SCE or SDG&E as compared to the CPP treatment groups. Additionally, the TOU households faced higher prices in the peak and lower prices in the off-peak during treatment. Therefore, the results for the degree of clustering must be interpreted with these caveats in mind.

As can be seen in Figures 1.8 and 1.9, in winter for the CPPH treatment group and summer for the CPPL treatment group there is clustering beyond that of the two counterfactuals right around zero (the kink). This is not the case in the summer for the CPPH treatment group and the winter for the CPPL treatment group. This is just as we predicted, as the winter for the CPPH and summer for the CPPL groups were when the households were most likely to be located close to the kink, and otherwise skewed into the loss domain. The width of each bar in the histograms is equal to \$4. Therefore, for the CPPH group in the winter season 10.04% more of the expenditure outcomes for treatment households were at the kink plus or minus \$6 than the control counterfactual. For the CPPL group in the summer months the results are similar (11.38% more for the treatment group than the control counterfactual outcomes are within \$6 of the kink). Additionally, consistently across the graphs there is a slight skewing of the treatment distributions to the left compared to the control counterfactual. This is in the direction of the gain domain.

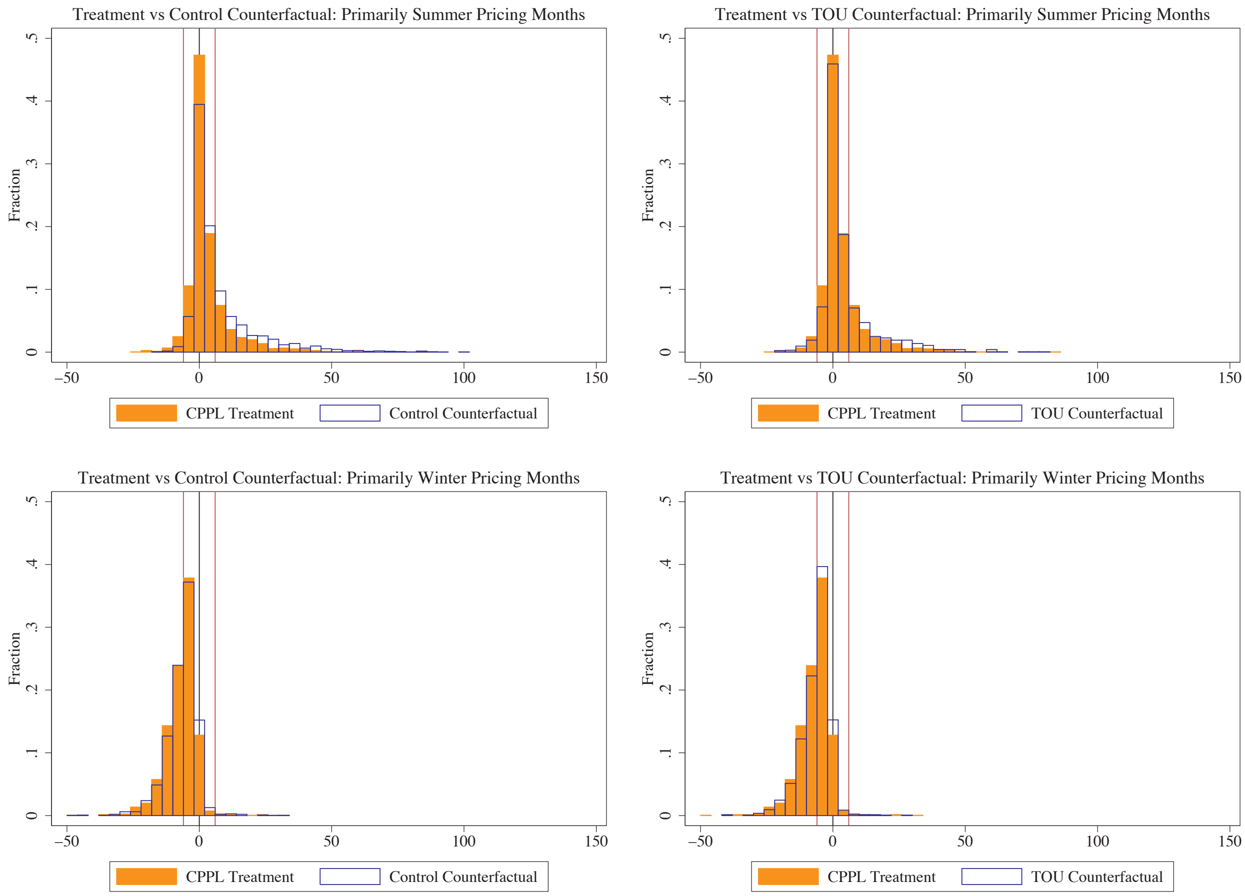
As was anticipated, the TOU households did tend to exhibit more clustering at the kink than the control counterfactual households. This may have been due to the selection issue, or due to the behavior induced by the TOU treatment prices. The CPPH treatment group had 3.58% more observations at the kink relative to the TOU counterfactual group during the winter pricing phase, and the CPPL treatment group had 4.74% more observations at the kink relative to the TOU counterfactual group during the summer pricing phases.

Figure 1.8: CPPH Bill Period Net Expenditure Clustering



Note: The solid histograms show the fraction of monthly net expenditure outcomes for the CPPH group in each \$4 bin. Net expenditure outcomes are defined as monthly observations of $y_{op}\,(p_{op} - p_r) + y_p\,(p_p - p_r)$. The outlined histograms show the hypothetical expenditure on the treatment tariffs less the true expenditure for the counterfactual households. Outcomes at zero are at the kink in the value function. The center vertical line is at zero, and the two outer vertical lines are at -6 and 6 respectively. Positive outcomes are in the loss domain, while negative outcomes are in the gain domain. Top panels: bill period in which more than 50% of the days were charged at summer prices, and uses the control (left) and TOU (right) households as counterfactuals. Bottom panels: bill periods that have more than half the days charged at winter prices, and uses the control (left) and TOU (right) households as counterfactuals.

Figure 1.9: CPPL Bill Period Net Expenditure Clustering



Note: The solid histograms show the fraction of monthly net expenditure outcomes for the CPPL group in each \$4 bin. Net expenditure outcomes are defined as monthly observations of $y_{op}\left(p_{op} - p_r\right) + y_p\left(p_p - p_r\right)$. The outlined histograms show the hypothetical expenditure on the treatment tariffs less the true expenditure for the counterfactual households. Outcomes at zero are at the kink in the value function. The center vertical line is at zero, and the two outer vertical lines are at -6 and 6 respectively. Positive outcomes are in the loss domain, while negative outcomes are in the gain domain. Top panels: bill period in which more than 50% of the days were charged at summer prices, and uses the control (left) and TOU (right) households as counterfactuals. Bottom panels: bill periods that have more than half the days charged at winter prices, and uses the control (left) and TOU (right) households as counterfactuals.

The question remains, is the degree of clustering observed for the CPPH group in the winter and CPPL group in the summer, statistically more than the clustering exhibited by the control or TOU counterfactuals? I tested this by bootstrapping the distribution of the fraction of observations within $6 of zero for the CPP, TOU and control households. I repeatedly resampled households with replacement for each group in each relevant time period to generate a distribution of the share of observations in the [-6,6] range around zero for each group.[19] A simple two-sample difference-in-means test, shown in Table 1.8, demonstrates that indeed the probability of outcomes being at the kink for the CPPL group in the summer and CPPH group in the winter are both statistically different from the corresponding control counterfactual probability. The probability for the TOU counterfactual and CPP treatments are closer to each other in all cases than for the control counterfactual. However, the degree of clustering for the CPPL treatment in the summer was significantly more than for the TOU counterfactual at just under the 95% confidence level. The difference between the CPPH and TOU distributions in the winter is not statistically significant.

Table 1.8: Bootstrapped Distributions of Outcome Probabilities at the Kink

	Treatment		Control		TOU		Treatment vs Control	Treatment vs TOU
	Mean	SD	Mean	SD	Mean	SD	t-stat	t-stat
CPPH Winter	0.705	0.019	0.605	0.019	0.670	0.024	-3.669	-1.125
CPPL Summer	0.767	0.020	0.647	0.032	0.718	0.023	-3.240	-1.636

Note: Bootstrapped mean and standard deviations of the probability that a net expenditure outcome will be within $6 of zero for the CPPH treatment in the winter pricing phase, and the CPPL treatment in the summer pricing phase. The standard deviations are clustered at the household level by construction in the bootstrapping process, and t-stat=$\frac{(Mean_{tr}-Mean_c)}{\sqrt{SD_{tr}^2+SD_c^2}}$, where tr and c indicate treatment and counterfactual, respectively.

Therefore, there is evidence that treatment households did exhibit statistically significant disproportionate clustering at the kink with respect to monthly expenditure – plus or minus $6 – during phases of the pricing tariffs that were more likely to place them close to the kink. This was particularly true for the CPPL treatment group, which exhibited statistically significantly more clustering than both the TOU and control counterfactuals in both summer pricing phases of the experiment. The CPPH treatment group did exhibit significantly more clustering than the control counterfactual group during the winter pricing phase of the experiment, but the difference in clustering between the CPPH and TOU counterfactual during the winter was not statistically significant.

[19] I drew the number of households in each treatment and pricing phase from the households in the data with replacement. I repeated this process 2000 times, recording the share of total observations with outcomes in the range [-6,6] for each case for all 2000 repetitions. The resulting set of 2000 data-points in each case made up the distribution of the probability of the share of households at the kink in each case, clustered at the household level.

1.4 Alternate Hypotheses

In the preceding sections I have demonstrated that consumers on the CPP treatment in the SPP experiment exhibited behavior consistent with a model of loss aversion over electricity expenditure. In this section I do the following: (i) test an alternative hypotheses that the disproportionate reduction in peak electricity consumption following more positive expenditure shocks in a given bill period reflects households learning new strategies for reducing peak consumption, and thereby can be explained by a reduction in the cost of reducing consumption during higher priced periods, and not necessarily a behavioral response to the higher probability of incurring a loss; (ii) test an alternative hypotheses that the disproportionate reduction in peak electricity consumption following more positive expenditure shocks in a given bill period is a result of households being budget constrained, and therefore facing high costs of overspending in a month, but does not necessarily reflect loss aversion, and (iii) explore whether there is evidence that households are unaware of precisely when their bill periods begin and end, which would suggest that narrow bracketing at the bill period level is an unreasonable assumption.

1.4.1 Learning Strategies to Reduce Peak Consumption

In Section 1.3.1 I showed that when households on the CPP experimental tariffs have experienced more critical peak days in a given bill period, they disproportionately cut back on subsequent peak electricity consumption in that bill period. This behavior is consistent with the model of loss aversion over electricity expenditure presented in this paper. However, if households learned better strategies for reducing peak electricity consumption the more critical peak days they experienced, this could also explain the empirical results presented above. In order to explore this question, I provide the results from two alternative specifications in Table 1.9: in the first, I control simply for the total number of critical peak days experienced so far in the pilot overall, and in the second I allow this variable to enter quadratically. If more critical peak days experienced overall resulted in statistically less peak electricity consumption during following peak periods, then one could conclude that the results presented above might be capturing this learning behavior more than behavior consistent with loss aversion. The results presented here are for the case with the control group as the counterfactual. I provide the results using the TOU group as the counterfactual in Appendix A.5.

The results from this analysis are quite interesting. First, when the overall past experience of critical peak days enters linearly – shown in Columns (2), (5) and (8) of Table 1.9 – the coefficients on this term are never significant, and additionally there is almost no difference in the $b_{5,p}$ coefficient on $T * D$. This provides more support to the loss aversion explanation than the learning explanation. However, when the experience of overall past critical peak days enters quadratically – presented in Columns (3), (6) and (9) – the story is even more interesting. Now the effect of more overall past experience of critical peak days is significant relative to the control group in all specifications. However, rather than more experience of critical peak days resulting in even less peak consumption, which would be consistent with learning, these results indicate that more critical peak days experienced overall is correlated with a subsequent increase in peak consumption relative to the control group. Because the sign of the coefficient on the quadratic term is negative it appears that this increase is happening at a decreasing rate. This is definitely inconsistent with learning better strategies to reduce peak consumption the more critical peak days the household has experienced. What then could explain these results?

Köszegi and Rabin (2006) have developed a model which suggests that consumers do not have a stagnant reference point, rather their reference point is updated based on expectations formed by recent experience. In the SPP pilot setting, if households became more accustomed to expenditure fluctuations as a result of critical peak days, then they may update their reference expenditure to reflect this the more experience they have on the experimental tariff. This updating of the reference point would explain a gradual relaxing of the degree to which households mitigate peak electricity consumption the more critical peak days to which they are exposed.

The total number of critical peak days experienced overall (denoted by E) and the number of critical peak days experienced so far in the bill period, or in the first week of the bill period, are correlated. In part because of this, the $b_{5,p}$ coefficient is no longer significant in regressions in Columns (3) and (6) relative to the control group, though the sign is still negative in all cases. However, in Column (9) we see that higher peak temperatures in the first week of the bill period still significantly correlates with lower subsequent peak consumption in the bill period relative to the control group, even when the overall number of critical peak days experienced is controlled for nonlinearly. This is consistent with household updating their reference point with respect to differentiated peak and off-peak prices, but still responding when there is a higher probability of a loss, even given an updated reference point, as a result of exogenous weather shocks.

This analysis suggests that learning better strategies to reduce peak consumption cannot explain the original results that households cut back on peak consumption after experiencing more critical peak days in a bill period. Rather, the results indicate that households may reduce the degree to which they are curbing peak consumption the more they get used to being charged higher peak prices, particularly in the form of experiencing more critical peak days overall. This is still consistent with households having loss-averse preferences, but suggests that they may be updating their reference point to reflect more familiarity with the dynamic pricing tariff.

Table 1.9: Learning vs Loss Aversion: CPP vs Control

Dependent Variable: Peak kWh									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T=1: CPP T=0: Control	D = Number of critical peak days so far			D = Number of critical peak days in week 1			D = Peak temerature in week 1		
	Original	E = overall number of critical days so far		Original	E = overall number of critical days so far		Original	E = overall number of critical days so far	
C ($b_{1,p}$)	1.027***	1.014***	0.992***	0.597***	0.601***	0.544***	0.571***	0.578***	0.554***
	(0.141)	(0.142)	(0.140)	(0.117)	(0.116)	(0.109)	(0.0990)	(0.0977)	(0.0960)
D ($b_{2,p}$)	0.0512*	0.0614**	0.0346	0.0584	0.0701	-0.00904	0.0991***	0.0996***	0.0947***
	(0.0286)	(0.0265)	(0.0259)	(0.0658)	(0.0628)	(0.0648)	(0.0128)	(0.0128)	(0.0133)
T * C ($b_{4,p}$)	-1.438***	-1.438***	-1.400***	-1.296***	-1.293***	-1.201***	-1.121***	-1.119***	-1.081***
	(0.191)	(0.192)	(0.187)	(0.173)	(0.170)	(0.159)	(0.141)	(0.139)	(0.136)
T * D ($b_{5,p}$)	-0.0914***	-0.0878***	-0.0378	-0.236***	-0.232***	-0.0982	-0.0661***	-0.0665***	-0.0582***
	(0.0345)	(0.0327)	(0.0307)	(0.0729)	(0.0696)	(0.0706)	(0.0168)	(0.0167)	(0.0176)
E		-0.00809	-0.0949***		-0.00682	-0.135***		-0.0134	-0.0839**
		(0.00881)	(0.0259)		(0.0102)	(0.0381)		(0.0104)	(0.0366)
E^2			0.00340***			0.00478***			0.00262**
			(0.000991)			(0.00134)			(0.00126)
T * E		-0.00189	0.114***		-0.00153	0.183***		0.00229	0.101**
		(0.0105)	(0.0320)		(0.0125)	(0.0447)		(0.0124)	(0.0433)
T * E^2			-0.00458***			-0.00702***			-0.00372**
			(0.00119)			(0.00163)			(0.00153)
Summer Pricing	-0.0896	-0.0917	-0.0789	0.118	0.116	0.140*	0.0993	0.0981	0.110
	(0.0743)	(0.0742)	(0.0743)	(0.0833)	(0.0831)	(0.0828)	(0.0847)	(0.0846)	(0.0844)
Peak Degree Hours	0.172***	0.172***	0.172***	0.191***	0.191***	0.191***	0.174***	0.174***	0.174***
	(0.00748)	(0.00748)	(0.00749)	(0.00803)	(0.00802)	(0.00802)	(0.00700)	(0.00700)	(0.00700)
Constant	4.235***	4.345***	3.343***	3.956***	4.051***	4.146***	3.411***	3.560***	2.462***
	(0.120)	(0.126)	(0.166)	(0.141)	(0.145)	(0.215)	(0.174)	(0.173)	(0.228)
Day-of-week effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-of-year effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Household fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Daily Observations	191,839	191,839	191,839	149,344	149,344	149,344	149,344	149,344	149,344
R-squared (within)	0.164	0.164	0.164	0.180	0.180	0.181	0.188	0.188	0.189
Number of Households	1,084	1,084	1,084	1,071	1,071	1,071	1,071	1,071	1,071

Standard errors clustered at household level in parentheses
*** p<0.01, ** p<0.05, *p<0.1

Note: Results of fixed-effect regressions exploring the correlation of daily peak kWh usage during a subsample of days in the experiment and a set of explanatory variables. The CPPL and CPPH treatment groups are pooled and the control group is used as the counterfactual. Columns (1), (4) and (7) reproduce the results of the original specifications from Table 1.3; Columns (2), (5) and (8) control for the total number of critical peak days experienced in the pilot overall (E), and Columns (3), (6) and (9) allow this variable to enter quadratically.

1.4.2 Constrained Budget

In this section I conduct an analysis designed to address the possible alternative explanation that households cut back on peak electricity consumption after previous positive shocks to expenditure in the bill period not because they are loss averse, but rather because they are budget constrained in such a way that they would face high costs to spending more than they are expecting to on electricity. I do this by allowing for heterogeneity of results across income levels, which addresses whether or not the results are driven by households being budget constrained in the following way: if households with lower incomes cut back on peak electricity consumption following positive shocks to expenditure more so than higher income households, then there is support for the hypothesis that this behavior is explained by households being budget constrained. However, if higher income households exhibit this behavior, it is harder to make the case that households avoid losses because of being budget constrained rather than because they are loss averse.

Income level is not observed for all households in the data, as it was obtained through a survey that was not returned by all participants. Table 1.10 presents a breakdown of the number of households with available income data by treatment. Over 80% of both CPP and TOU households completed the income portion of the survey and just under 70% did for the control group. The majority of households, around 68%, made below $75,000 per year.

Table 1.10: Number of Households with Income Data by Income Bracket

Annual Income Level	**CPP**	**TOU**	**Control**
Income < $25,000	137 (25%)	50 (25%)	59 (21%)
$25,000 < Income < $50,000	136 (25%)	47 (23%)	64 (23%)
$50,000 < Income < $75,000	101 (18%)	42 (21%)	65 (23%)
$75,000 < Income < $100,000	71 (13%)	25 (12%)	32 (11%)
$100,000 < Income < $150,000	62 (11%)	19 (9%)	38 (13%)
$150,000 < Income	44 (8%)	18 (9%)	25 (9%)
Total Number of Households with Income Data:	551	201	283
Share of Total Number of Households in Sample:	0.83	0.84	0.68

Table 1.11 presents the results of this analysis using the control group as the counterfactual. Results with the TOU group as the counterfactual can be seen in Appendix A.5. Looking at Table 1.11 we see that households in the lowest income bracket appear to have the most inelastic peak electricity consumption; they do not change consumption much even as a result of critical peak days. There is no evidence that households in the lowest two brackets of income disproportionately reduce peak consumption when there have been positive shocks to electricity expenditure. However, households in the fourth ($75,000 to $100,000 per year), sixth (more than $150,000 per year), and marginally the third ($50,000 to $75,000 per year) income brackets appear to drive the result; households in these three mid-high income brackets do cut back on peak consumption following previous positive shocks to electricity expenditure that bill period. This does not support the hypothesis that this behavior is being driven by households with a binding monthly budget constraint that would cause them to face high penalties if they overspent on electricity, as electricity expenditure for the households exhibiting this behavior constitutes at most around 2% of monthly household income. These results therefore support the hypothesis that this pattern is due to behavioral factors, such as loss aversion, and not because households need to avoid overspending on electricity because of other constraints.

Table 1.11: Budget Constrained vs Loss Aversion: CPP vs Control

Dependent Variable: Peak kWh						
	(1)		(2)		(3)	
T=1: CPP T=0: Control	D = Number of critical peak days so far		D = Number of critical peak days in week 1		D = Peak temerature in week 1	
C * (Income<25,000)	0.195	(0.433)	-0.123	(0.345)	0.0867	(0.273)
C * (25,000<Income<50,000)	0.496	(0.325)	0.252	(0.303)	0.350	(0.262)
C * (50,000<Income<75,000)	1.482***	(0.363)	1.250***	(0.381)	1.034***	(0.294)
C * (75,000<Income<100,000)	1.568***	(0.523)	1.439**	(0.584)	1.349***	(0.469)
C * (100,000<Income<150,000)	1.792***	(0.666)	1.079**	(0.484)	1.030**	(0.420)
C * (150,000<Income)	1.680***	(0.634)	0.662	(0.452)	0.612	(0.408)
D * (Income<25,000)	0.0136	(0.0727)	-0.0262	(0.149)	0.0298	(0.0344)
D * (25,000<Income<50,000)	-0.0350	(0.0567)	-0.00613	(0.119)	0.0475***	(0.0166)
D * (50,000<Income<75,000)	0.134*	(0.0696)	0.264	(0.167)	0.132***	(0.0338)
D * (75,000<Income<100,000)	0.290***	(0.0924)	0.410**	(0.181)	0.196***	(0.0471)
D * (100,000<Income<150,000)	0.0492	(0.0894)	-0.0963	(0.152)	0.147***	(0.0426)
D * (150,000<Income)	0.0836	(0.121)	-0.102	(0.235)	0.130***	(0.0285)
T * C * (Income<25,000)	-0.552	(0.487)	-0.584	(0.391)	-0.593*	(0.306)
T * C * (25,000<Income<50,000)	-1.308***	(0.362)	-1.166***	(0.351)	-1.064***	(0.309)
T * C * (50,000<Income<75,000)	-1.761***	(0.476)	-1.909***	(0.500)	-1.588***	(0.385)
T * C * (75,000<Income<100,000)	-1.980***	(0.573)	-2.043***	(0.641)	-1.769***	(0.521)
T * C * (100,000<Income<150,000)	-1.415*	(0.774)	-1.339**	(0.586)	-1.507***	(0.513)
T * C * (150,000<Income)	-2.213***	(0.719)	-1.483**	(0.578)	-1.387***	(0.515)
T * D * (Income<25,000)	-0.0570	(0.0815)	-0.152	(0.165)	-0.0152	(0.0382)
T * D * (25,000<Income<50,000)	-0.00705	(0.0682)	-0.183	(0.141)	-0.0292	(0.0229)
T * D * (50,000<Income<75,000)	-0.128	(0.0888)	-0.353*	(0.208)	-0.0853*	(0.0448)
T * D * (75,000<Income<100,000)	-0.323***	(0.105)	-0.602***	(0.203)	-0.174***	(0.0523)
T * D * (100,000<Income<150,000)	0.0552	(0.118)	0.255	(0.225)	0.00143	(0.0545)
T * D * (150,000<Income)	-0.294**	(0.141)	-0.512*	(0.273)	-0.0945**	(0.0446)
Summer Pricing	-0.109	(0.0778)	0.0762	(0.0908)	0.0563	(0.0932)
Peak Degree Hours	0.172***	(0.00798)	0.190***	(0.00848)	0.174***	(0.00742)
Constant	4.218***	(0.130)	3.972***	(0.154)	3.412***	(0.186)
Day-of-week effects	Y		Y		Y	
Month-of-year effects	Y		Y		Y	
Household fixed effects	Y		Y		Y	
Daily Observations	158,567		123,638		123,638	
R-squared (within)	0.167		0.182		0.196	
Total Number of Households	831		822		822	

Standard errors clustered at household level in parentheses
*** p<0.01, ** p<0.05, *p<0.1

Note: Results of fixed-effect regressions exploring the correlation of daily peak kWh usage during a subsample of days in the experiment and a set of explanatory variables. The CPPL and CPPH treatment groups are pooled and the control group is used as the counterfactual. Results are differentiated across six income brackets. The analysis is limited to households who provided answers to the income question in the survey (83% of CPP households and 68% of control households).

1.4.3 Unaware of Bill Period Dates

Finally, in this section I examine the assumption that households are narrowly bracketing at the bill period level in more detail. Indeed it is unclear whether households would be aware of precisely when their bill period starts and stops each month. To explore this question I artificially perturb all bill periods by shifting the start/stop days of the bill periods back 14 days and then repeat the analysis. If the $b_{5,p}$ coefficient were not significant or of a lower magnitude than in the original analysis, this would suggest that households were adjusting their behavior within each bill period in a sophisticated way indicating that they were both behaving in a way that is consistent with loss aversion, and narrowly bracketing at a bill period level.

Results of this analysis relative to the control group are presented in Table 1.12. Results relative to the TOU group can be found in Appendix A.5. Looking at Table 1.12, it is clear that the $b_{5,p}$ coefficient is relatively consistent even after the bill period definition has been shifted. This calls into question the assumption that households are successfully narrowly bracketing at the bill period level. It is important to note, however, that this is not a perfect falsification of narrow bracketing at the bill period level. Depending on when the critical peak days occurred in the bill period, and the correlation with the occurrence of later critical peak days and temperature fluctuations, it is hard to truly disentangle the behavior in this way. However, it does appear that households are responding to past critical peak days and high temperatures in peak periods by reducing peak consumption for the several weeks thereafter, but not necessarily only within the same bill period. This is not inconsistent with loss aversion if indeed households weren't sure when their bill periods started or stopped. If households responded to positive shocks to electricity expenditure by cutting back on peak consumption within the next few weeks, that would be a reasonable heuristic if the ultimate goal were to avoid bill period losses.

Table 1.12: Artificially Shifted Bill Periods: CPP vs Control

Dependent Variable: Peak kWh						
	(1)	(2)	(3)	(4)	(5)	(6)
T=1: CPP T=0: Control	D = Number of critical peak days so far		D = Number of critical peak days in week 1		D = Peak temerature in week 1	
	Original	Shift bill period by two weeks	Original	Shift bill period by two weeks	Original	Shift bill period by two weeks
C ($b_{1,p}$)	1.027***	0.968***	0.597***	0.668***	0.571***	0.604***
	(0.141)	(0.136)	(0.117)	(0.140)	(0.0990)	(0.124)
D ($b_{2,p}$)	0.0512*	0.0878***	0.0584	0.101	0.0991***	0.101***
	(0.0286)	(0.0300)	(0.0658)	(0.0695)	(0.0128)	(0.0146)
T * C ($b_{4,p}$)	-1.438***	-1.358***	-1.296***	-1.412***	-1.121***	-1.214***
	(0.191)	(0.185)	(0.173)	(0.192)	(0.141)	(0.164)
T * D ($b_{5,p}$)	-0.0914***	-0.135***	-0.236***	-0.214***	-0.0661***	-0.0710***
	(0.0345)	(0.0364)	(0.0729)	(0.0760)	(0.0168)	(0.0185)
Summer Pricing	-0.0896	-0.0894	0.118	0.0684	0.0993	0.0194
	(0.0743)	(0.0743)	(0.0833)	(0.0928)	(0.0847)	(0.0951)
Peak Degree Hours	0.172***	0.172***	0.191***	0.189***	0.174***	0.171***
	(0.00748)	(0.00748)	(0.00803)	(0.00821)	(0.00700)	(0.00726)
Constant	4.235***	4.234***	3.956***	3.524***	3.411***	2.997***
	(0.120)	(0.120)	(0.141)	(0.115)	(0.174)	(0.152)
Day-of-week effects	Y	Y	Y	Y	Y	Y
Month-of-year effects	Y	Y	Y	Y	Y	Y
Household fixed effects	Y	Y	Y	Y	Y	Y
Daily Observations	191,839	191,839	149,344	133,247	149,344	133,247
R-squared (within)	0.164	0.164	0.180	0.182	0.188	0.190
Number of Households	1,084	1,084	1,071	1,073	1,071	1,073

Standard errors clustered at household level in parentheses

*** p<0.01, ** p<0.05, *p<0.1

Note: Results of fixed-effect regressions exploring the correlation of daily peak kWh usage during a subsample of days in the experiment and a set of explanatory variables. The CPPL and CPPH treatment groups are pooled and the control group is used as the counterfactual. Columns (1), (3) and (5) reproduce the results of the original specifications from Table 1.3, and Columns (2), (4) and (6) show the results after the definition of the bill period has been artificially shifted back 14 days for each bill period for each household.

1.5 Conclusion

In this study I specified a model of loss aversion over electricity expenditure. I used this model as a basis to derive testable predictions for consumption behavior of households on two critical peak pricing experimental tariffs. I use independent variation in the number of critical peak days called within a bill period and the peak temperature in the bill period, which are positively correlated with the probability of ending up in the loss domain of reference-dependent utility; when households are more likely to be in the loss domain, they respond by more strongly cutting back on peak consumption during subsequent peak hours in that bill period. The magnitude of the additional reduction in peak consumption relative to the control counterfactual group was 1.69% for each additional critical peak day experienced so far in the bill period; 4.37% for each additional critical peak day experienced in the first week of the bill period, and 1.22% for each additional peak degree-hour experienced in the first week of the bill period. These magnitudes relative to the TOU counterfactual group were 1.58% and 3.15% for the number of critical peak days experienced so far in the bill period, and in the first week of the bill period, respectively. The results for the average peak degree-hours in the first week of the bill period were not significant relative to the TOU counterfactual group.

Additionally, I show evidence of disproportionate clustering of monthly expenditure at the kink in the reference-dependent value function during pricing phases that placed households close to the kink, and particularly that otherwise would have skewed them into the loss domain.

I explore two alternative explanations for this behavior other than loss aversion. First, I show that the reduction in peak consumption following positive shocks to electricity expenditure does not appear to be a result of households learning new strategies for reducing peak consumption the more critical peak days they experience overall. Indeed, treatment households actually appeared to increase their peak consumption, at a decreasing rate, the more critical peak days they experienced overall during the pilot. This behavior is not only counter to a learning explanation, but is consistent with households updating their reference point over time. Second, I show that households exhibiting the strongest behavior of reducing peak consumption following positive expenditure shocks tended to be mid-high income households, for whom electricity expenditure only constitutes at most around 2% of monthly income, indicating that this behavior does not appear to be explained by households being severely budget constrained such that they would incur a high penalty if they overspent on electricity.

Finally, I test the validity of the assumption that households are narrowly bracketing at the bill period level; it does appear that households are not narrowly bracketing at the bill period level in a clean and sophisticated way, but instead they appear to reduce peak consumption in the several weeks following past positive expenditure shocks whether or not those weeks are in the same bill period. This is not inconsistent with loss aversion if we assume households are unaware of exactly when their bill periods stop and start, but rather attempt to avoid bill period losses using a heuristic of responding to positive expenditure shocks by then reducing expenditure in the following few weeks.

In essence these results demonstrate that the occurrence of critical peak days did not only result in a reduction of peak consumption on that day, but also spilled over to further reduction of peak consumption on regular peak days for several weeks thereafter. This was similarly true when temperatures were high during high priced periods. This form of demand adjustment resulted in households experiencing bill-period expenditures equal to what they would have paid on the standard non-dynamic pricing tariff at a disproportionate rate. This higher number of bill periods with equal expenditure displaced bill periods in which they otherwise would have paid more than if they were on standard pricing.

The results from this analysis, indicating the presence of loss aversion over electricity expenditure in the pattern of electricity consumption behavior, are relevant for the design and implementation of dynamic pricing structures in general. First, the documented greater effectiveness of CPP as compared to TOU or Peak Time Rebate structures found in a number of pilots, is explained somewhat by the presence of loss aversion, as the intermittence of significantly higher prices called during critical peak days on CPP tariffs creates variation in monthly expenditure in the loss domain of consumers' reference-dependent value function. This underscores the value of a pricing structure such as CPP from the perspective of long-term efficiency and sustainability of the electricity grid. Second, while CPP tariffs have been shown to be widely effective at reducing peak consumption, there is concern that consumers dislike them, and so would resist mandatory or opt-out CPP tariffs, and would be reluctant to opt-in to optional CPP tariffs. This dislike may stem from, in part, the comparison between the status-quo reference expenditure and the expenditure on a CPP pricing structure. A loss averse consumer would be more likely to dislike a CPP pricing structure because of the nature of the variation in expenditure on these structures. However, policies that would allow consumers to ease into the experience of a CPP structure, or ones that would update their reference-point in advance by providing "shadow" bills showing how much consumers on the status-quo tariff would be paying on the CPP tariff, would be expected to reduce the resistance to a CPP tariff. Another option might be to manipulate the narrowness of the reference bracket households are focusing on when deciding whether to sign on to a CPP pricing structure. If consumers were not shown a monthly shadow bill for a CPP pricing structure, but rather were told how much they would have saved over the year, which is more likely to be positive, it might reduce the resistance to such an option.

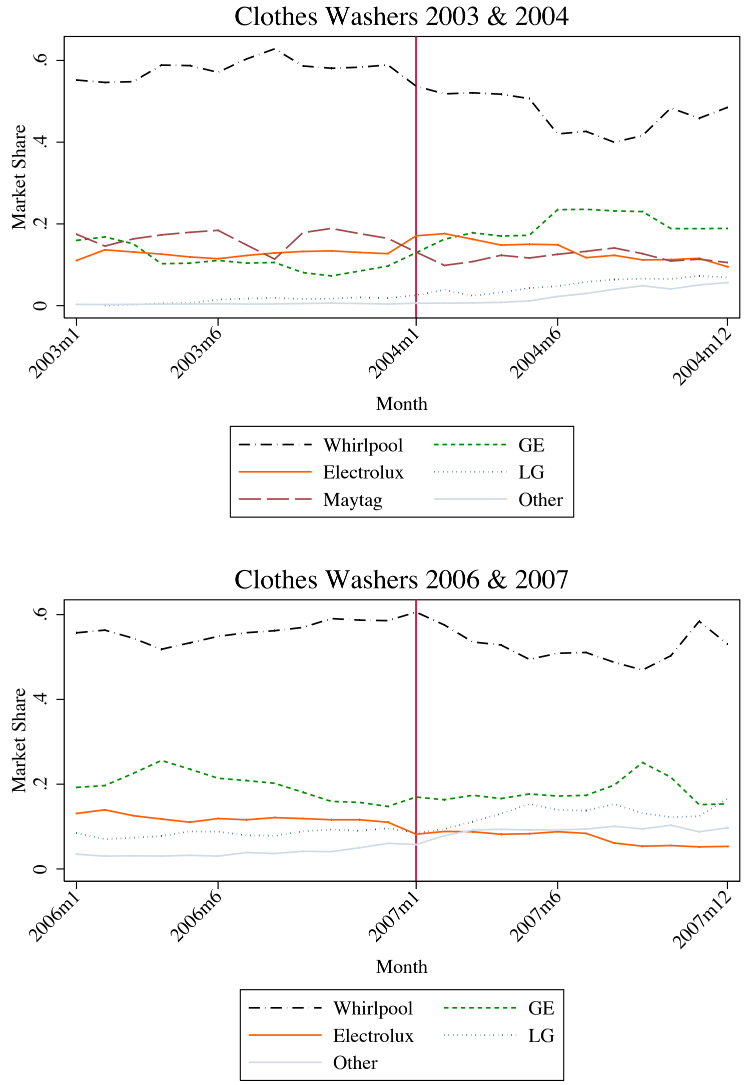
Chapter 2: Appliance Efficiency Standards and Price Discrimination

Minimum efficiency standards for household appliances address several market failures including environmental externalities, information asymmetries, principal-agent problems, consumer biases, and imperfect competition. Chen, Dale, and Roberts (2013) found a 2007 restriction in efficiency standards for clothes washers corresponded with dropping clothes washer prices on average. While they mention imperfect competition as one possible explanation for this phenomenon, they put aside the question of market structure and while assuming prices dropped as a result of economies of scale in production, go on to estimate consumer welfare benefits of the standard change. I return to the question of market structure and directly test whether imperfect competition explains these price drops.

The markets for large energy consuming appliances are likely oligopolistic or monopolistically competitive, rather than perfectly competitive. Market shares for many energy consuming durables are increasingly controlled by a shrinking handful of manufacturers. For clothes washers – the focus of this paper – these manufacturers are primarily Whirlpool, Electrolux, GE, and increasingly LG. Whirlpool merged with Maytag in 2006, and Ashenfelter, Hosken, and Weinberg (2011) show that the result was an increase in price and decrease in product variety for some appliances, an outcome consistent with consolidating market power. Indeed, in data used for this paper Whirlpool – including its subsidiary brands – controlled close to 60% of the clothes washer market. Figure 2.1 shows the market shares of the largest manufacturers during my study period. Even given this level of consolidation, it is difficult to demonstrate that firms are exercising market power in pricing using only market equilibrium prices and quantities.

I demonstrate that market responses to increasingly stringent standards were more consistent with a market made up of price discriminating producers, as opposed to a perfectly competitive market. I use point-of-sale (POS) data for clothes washers spanning two changes to minimum efficiency standards, one on January 1st, 2004 and one on January 1st, 2007. Energy Star standards changed at each of these dates as well. I show that clothes washer prices experienced both an immediate level drop, as well as a downward break in trend, at the effective dates of both new standards. In particular, the prices of mid-low efficiency products showed the largest immediate level drop – a pattern consistent with price discrimination. In a perfectly competitive market, in contrast, prices of mid-low efficiency models should increase following a tightening standard. The downward trend-break tended to be larger in magnitude for higher efficiency models. Additionally, I demonstrate that the new standards were associated with increased model proliferation within the highest efficiency categories. Finally, I show that firms apparently used different strategies to respond to these two changes in standards: at the 2004 standard change, many existing models were modified and reintroduced into the market, indicating possible "low-hanging fruit" in terms of inexpensive efficiency improvements. This revamping of existing stock did not appear as prevalent in 2007.

Figure 2.1: Market Share by Manufacturer in Study Period



Note: Market share as measured in the NPD data of the largest manufacturers in the time periods just around the standard change dates for clothes washers. The four largest manufacturers of clothes washers are Whirlpool, GE, Electrolux, and increasingly LG. Maytag was a major manufacturer prior to 2006, at which point they merged with Whirlpool. The depicted market share for Whirlpool includes all its subsidiary brands appearing in the NPD data (Estate, Inglis, Roper and KitchenAid, as well as Maytag and its subsidiary brands Amana and Magic Chef after 2006). GE's market share includes sales by its subsidiary brands (Hotpoint and Ariston). Electrolux's market share includes sales by its subsidiary brands (Frigidaire, Westinghouse and White Westinghouse). All other manufacturers represented in the data are aggregated into the "Other" category (Electro Brand, Equator Appliances, Eurotec, Fagor, Fisher & Paykel, Haier, Koblenz, Miele, Samsung, Speed Queen, and Summit).

This paper will proceed as follows: Section 2.1 outlines the history of relevant minimum and Energy Star standard changes; Section 2.2 outlines the model and derives testable predictions; Section 2.3 describes the data; Section 2.4 describes the estimation strategy and presents the results of the analysis, and Section 2.5 concludes.

2.1 Minimum Energy Efficiency and Energy Star Standards

In 1987 the National Appliance Energy Conservation Act (NAECA) established legislation stipulating that minimum efficiency for clothes washers – among other products – manufactured for sale in the United States undergo periodic restriction. Also in 1987 Congress adopted the first such federal standard for clothes washers to be effective in 1988. The DOE adopted the second federal clothes washer standard in 1991, which went into effect in 1994. This analysis focuses on the third federal clothes washer standard, which the DOE adopted in 2001, and went into effect in a two-tier process. The first phase was effective on January 1st, 2004, and the second phase on January 1st, 2007. Clothes washers are also subject to a labeling standard by Energy Star. This is not a restrictive standard, but rather establishes a benchmark of efficiency such that products exceeding that benchmark qualify for the Energy Star label, signaling a model as highly efficient to potential customers.

Table 2.1 provides a breakdown of the minimum and Energy Star standards for clothes washers enacted between 1991 and 2007. Before 2004, the minimum standard was based on the Energy Factor (EF), which measures efficiency in terms of cubic feet per kWh per cycle. In 2004 the criteria for meeting the minimum standard became based on the Modified Energy Factor (MEF). The MEF, also measured in cubic feet per kWh per cycle, added to the EF by incorporating the energy required to dry moisture remaining in the clothing following the final spin cycle. On January 1st, 2004, the clothes washer standard changed, requiring that the MEF be no less than 0.65 for compact models, and 1.04 for standard-class (both top- an front-load) models. Simultaneously the Energy Star standard (only established for standard-class models) restricted the minimum MEF cut-off Energy Star qualification from 1.26 to 1.42. Then, on January 1st, 2007, the minimum standard was further restricted for standard-class top- and front-load models, requiring the MEF be no less than 1.26. The Energy Star standard also increased on January 1st, 2007, requiring the MEF be no less than 1.72, and now also requiring these models have a Water Factor (WF) of no more than 8.0. The WF is the number of gallons per cycle per cubic foot used by the washer.

Table 2.1: Clothes Washer Minimum and Energy Star Standards between 1991 and 2007

Adopted Date	Effective Date	Minimum Efficiency Requirement			Energy Star Requirement
		Compact Top Load	Standard Top Load	Front Load	
1991	1994	EF$\geq$0.9	EF$\geq$1.18	-	-
2001	2001	-	-	-	MEF$\geq$1.26
2001	2004	MEF$\geq$0.65	MEF$\geq$1.04	MEF$\geq$1.04	MEF$\geq$1.42
2001	2007	(no change)	MEF$\geq$1.26	MEF$\geq$1.26	MEF$\geq$1.72 & WF$\leq$8.0

Note: As of 1994 the minimum standard was based on the Energy Factor (EF) which measures overall washer efficiency in terms of cubic feet per kWh per cycle. As of 2004 the minimum standard became based on the Modified Energy Factor (MEF) which is also measured in cubic feet per kWh per cycle, but takes into account not only the machine electrical energy and water heating energy, but also the energy required for moisture removal, whereas the EF did not account for this additional drying energy. Starting in 2007, the Energy Star criteria also included a requirement based on the Water Factor (WF) which is the number of gallons per cubic foot per cycle that the clothes washer uses. Compact models are models less than 1.6 cubic feet and standard-class models are larger than 1.6 cubic feet. During this time there was no Energy Star criteria for compact models, only standard-class models.

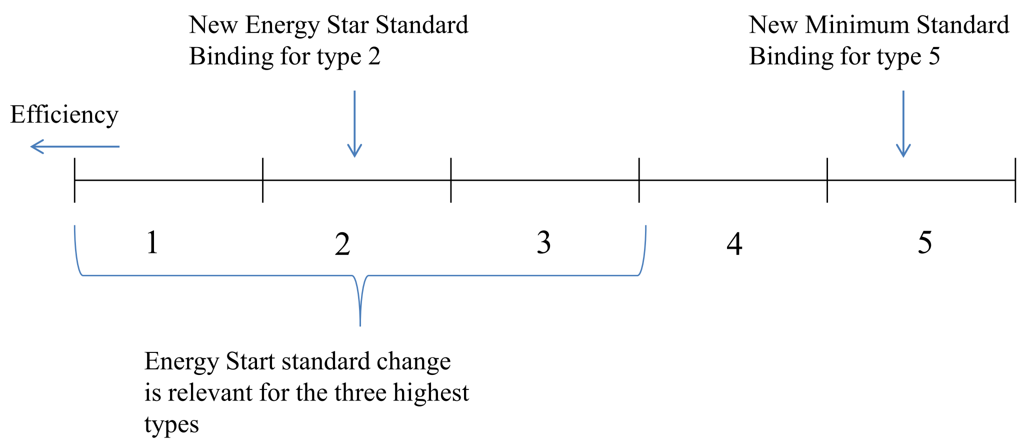
2.2 Model of Consumer Durables and Market Power

In this section I present and extend a classic model of second-degree price discrimination for a quality-differentiated set of durable goods. I extend the model slightly to fit the setting of a simultaneous change in the minimum and Energy Star standards of clothes washers. The model provides predictions about how the standard changes should affect the market prices and innovation patterns of clothes washers in a market with price discrimination as compared to perfect competition.

There is an extensive theoretical literature discussing price discrimination with quality differentiation in imperfectly competitive markets. The classic result is a monopoly engaging in second-degree price discrimination, thereby inducing consumers to sort themselves into purchasing the product targeting their willingness to pay level. In this way the monopolist can extract more consumer surplus than if they supplied only one product type, or the socially optimal menu of products. Mussa and Rosen (1978) provide the original model with a monopoly supplier and a continuous distribution of consumer preferences for quality. Most papers that discuss this model simplify by using two consumer types. I assume five consumer types – summarized in Figure 2.2 – because when both the minimum and Energy Star standards change simultaneously in my setting, there will be dynamic changes across the market efficiency spectrum in a slightly more complicated way than can be approximated with two consumer types.

I define the consumer preference heterogeneity by assuming five consumer types, where type 1 has the highest valuation for efficiency, and type 5 has the lowest. The market will therefore consist of five efficiency segments corresponding to the five consumer types. Assume the Energy Star standard will only impact the highest efficiency market segments, here consisting of types 1, 2 and 3.[20] Assume segment 1 consists of all products that are Energy Star certified both before and after the new standard; segment 2 consists of all products that were Energy Star certified but are decertified as a result of the new Energy Star standard, and segment 3 consists of high-end products that are never Energy Star certified, but are the closest substitutes to the newly decertified segment 2 products. Then, at the lower end of the market, assume segment 5 consists of models that will be directly affected by a tightened minimum efficiency standard, and segment 4 are mid-low end products that are the closest substitutes to the directly affected segment 5 products. These market segments are depicted in Figure 2.2.

Figure 2.2: Definition of Energy Efficiency-Based Market Segments/Consumer Types



Note: Definition of the market segments/consumer types in terms of energy efficiency categorizations used in this model. Each efficiency category/market segment will correspond with a consumer "type" based on that type's preferences for efficiency. Consumers of type 5 have the lowest willingness to pay for energy efficiency while consumers of type 1 have the highest willingness to pay for efficiency. A change in the Energy Star standard is assumed to directly affect market segment/consumer type 2. A change in the minimum standard is assumed to be binding for market segment/consumer type 5.

In the following sections I outline the model and derive testable predictions: in Section 2.2.1 I present the basic model of a price discriminating monopolist facing these five consumer types and outline the predictions of how a minimum standard change alone will affect prices; in Section 2.2.2 I extend the model and outline the predictions of how a change in the Energy Start standard alone will affect prices; in Section 2.2.3 I discuss the implication of the market being oligopolistic or monopolistically competitive, rather than monopolistic; in

[20]Note that it is likely that this heterogeneity among the highest type of the consumers is relevant; the Consortium for Energy Efficiency (CEE) rates appliances that are all Energy Star qualified into three additional energy efficiency tiers. These higher efficiency tiers often indicate the level of future Energy Star standards. Also, some have suggested that consumers tend to be more brand-conscious at the high efficiency end of the spectrum of the market (Katz, 1984). It therefore stands to reason that those consumers might also be more conscious of small variation in other important model characteristics as well, such as energy efficiency.

Section 2.2.4 I outline the testable predictions from the model to show the effect on prices of a simultaneous change in both the minimum and Energy Star standards by combining the predictions from Sections 2.2.1 and 2.2.2, and finally in Section 2.2.5 I discuss two other testable predictions of a minimum standard change in this model.

2.2.1 Monopoly Price Discrimination and Minimum Standard Change

I present here a simple reproduction, with five discrete types of consumers, of the key aspects of the classic Mussa and Rosen (1978) monopoly price discrimination model, pulling heavily from the characterization used by others (e.g. Donnenfeld and White, 1988; Ronnen, 1991; Fischer, 2005; Houde, 2012).[21] I then outline, following Fischer (2005), the result of imposing a minimum standard in this model.

Assume consumers have unit demand for a good, here an energy consuming durable such as a clothes washer. This means that each consumer will purchase at most one unit of the good. Assume five types of consumers – high (type 1) to low (type 5)– characterized by having different willingness to pay for efficiency; assume θ^k is the valuation of consumer type k for efficiency e where, without loss of generality, $\theta^5 < \theta^4 < \theta^3 < \theta^2 < \theta^1$. In equilibrium there will be five models of clothes washers provided by the market, indexed by j, which vary over efficiency level (e_j) and price (p_j). Utility of consumer k for model j is:

$$U_{kj} = \theta^k e_j - p_j$$

where:

$$\theta^k \in \{\theta^5, \theta^4, \theta^3, \theta^2, \theta^1\} = \text{valuation of energy efficiency } e \text{ of the three consumer types}$$
$$e_j = \text{energy efficiency level of model } j$$
$$p_j = \text{purchase price of model } j$$

Suppose there are N consumers and $s_k N$ have valuation θ^k, where $\sum_{k=1}^{5} s_k = 1$. The monopolist does not observe a consumer's type, so they cannot perfectly price discriminate. Assume the cost of producing energy efficiency level e_j is $c(e_j)$, and that $c(e_j) \geq 0$, $c'(e_j) \geq 0$ and $c''(e_j) > 0$.[22] Note that I'm using k to index consumer types and j to index model types. In equilibrium each model type will correspond to one consumer type, so k and j will be equivalent. At this point I make this explicit by indexing everything by j.

Before looking at the monopoly case, I first show what the social welfare maximizing/perfectly competitive price and efficiency schedule would be in this simple model. A social planner would choose the efficiency levels to maximize total welfare. They would therefore solve the optimization problem presented in Equation 2.1.

$$\max_{e_1,e_2,e_3,e_4,e_5} W = \sum_{j=1}^{5} s_j \cdot \left(\theta^j e_j - c(e_j)\right) \tag{2.1}$$

[21] A more step-by-step derivation of the model for three consumer types, which is easily extended to any discrete number of types, is provided in Appendix B.1.

[22] The choice of a strictly convex cost of quality (or alternatively a concave-in-quality objective function of the firm through some other input to profit) is a necessary condition for a separating price discrimination equilibrium to be optimal for the monopolist (Salant, 1989).

The first order conditions for the social planner are shown in Equation 2.2.

$$c'\left(e_j^*\right) = \theta^j,\ \forall j \in \{1,2,3,4,5\} \tag{2.2}$$

This implies that the social planner would choose to increase the efficiency for each model up until the point that the marginal cost of producing that level of efficiency just equals the marginal consumer valuation. While consumer demand is perfectly inelastic, in a perfectly competitive setting with free entry of new firms, price above marginal cost would result in excess supply. Therefore the optimal prices are also equal to marginal cost. This result is shown in Equation 2.3.

$$c'\left(e_j^*\right) = p_j^*,\ \forall j \in \{1,2,3,4,5\} \tag{2.3}$$

Now I turn to the monopoly case. The monopolist picks the levels of efficiency and price (e_j, p_j) for each of its five models in order to maximize profit. They want to impose a price-efficiency schedule that will extract the maximum consumer surplus from all five types of consumer. If the monopolist could perfectly price discriminate, they would price so as to extract all consumer surplus. Therefore they would have an incentive to provide the social welfare maximizing level of efficiency $c'\left(e_j^{PD}\right) = \theta^j,\ \forall j \in \{1,2,3,4,5\}$, where e_j^{PD} is the monopoly's optimal choice of energy efficiency to sell to consumer type j if they could perfectly price discriminate. In order to extract all the consumer surplus, they would set price just such that each consumer's utility is equal to zero, meaning that consumers would just be indifferent between purchasing and not purchasing the product. However, if the monopolist cannot identify which consumer is which, and they simply provide an efficiency-price schedule consisting of the socially optimal levels of efficiency sold at prices such that $U^j = \theta^j e_j^{PD} - p_j = 0$ for each level of $e_j^{PD},\ \forall j \in \{1,2,3,4,5\}$, the outcome would not be an equilibrium. This is because, for example, the type 4 consumer will not follow through on purchasing the type 4 product, but would rather choose to purchase the lowest type product; if the type 4 consumer purchases the type 4 product, they will have utility equal to zero, but if they purchase the lowest type model they will have utility greater than zero. Therefore, the monopolist will not actually succeed in achieving their maximum profit using this strategy.

In the case where the monopolist cannot identify which type of consumer is which, they can't perfectly discriminate, but rather will engage in imperfect – or second-degree – price discrimination. In order to do this they will maximize their profit subject to two sets of constraints. The first set, the Individual Rationality (IR) constraints, guarantee that all five types of consumers are willing to purchase a product at all.[23] The second set of constraints are the Incentive Compatibility (IC) constraints, also known as the self-selection constraints. These constraints guarantee that each type is only willing to purchase the model type intended for them, and not the model type intended for any of the other types of consumers.

[23]There could also be a case where the monopolist would find it more profitable to only sell to a subset of consumer types in which case we would not require that the IR constraint for all types hold. For the time being I assume away this case and assume the valuations of all consumer types and production costs are such that the monopolist finds it profitable to serve all consumer types.

Therefore, the monopolist chooses the efficiency levels and prices of the five types of models they supply by maximizing their profit subject to the IRj and ICj_k constraints, where IRj refers to the IR constraint for the type j consumer, and ICj_k refers to the IC constraint assuring that consumer type j will be unwilling to purchase product type $k \neq j$ in equilibrium. In a separating equilibrium (i.e. $p_j \neq p_k$ and $e_j \neq e_k \; \forall j \neq k$) then $\theta^1 > \theta^2 > ... > \theta^5$ implies that $IR5$, $IC1_2$, $IC2_3$, $IC3_4$ and $IC4_5$ are binding while all other IR and IC constraints are non-binding.[24] Therefore the monopolist's problem simplifies to the that in Equation 2.4.

$$
\begin{aligned}
\max_{p_1,p_2,\ldots,p_5,e_1,e_2,\ldots,e_5} \pi = \sum_{j=1}^{5} s_j \cdot (p_j - c\,(e_j)) \\
s.t. \\
IR5 :& \theta^5 e_5 - p_5 = 0 \\
ICi_{j+1} :& \theta^j e_j - p_j = \theta^j e_{j+1} - p_{j+1}, \forall j \in \{1,2,3,4\}
\end{aligned}
\tag{2.4}
$$

The solution for the monopolist under second-degree price discrimination $(\bar{e}_j, \bar{p}_j)$, $\forall j \in \{1,2,3,4,5\}$, is presented in Equation System 2.5.

$$
\begin{aligned}
c'(\bar{e}_j) =& \theta^j - \frac{\sum_{k=1}^{j-1} s_k}{s_j} \left(\theta^{j-1} - \theta^j\right),\; \forall j \in \{2,3,4,5\} \\
c'(\bar{e}_1) =& \theta^1 \\
\bar{p}_5 =& \theta^5 \bar{e}_5 \\
\bar{p}_j =& \bar{p}_{j+1} + \theta^j \left(\bar{e}_j - \bar{e}_{j+1}\right),\; \forall j \in \{1,2,3,4\}
\end{aligned}
\tag{2.5}
$$

These results, consistent with Mussa and Rosen (1978), indicate that the second-degree price discriminating monopolist distorts downward the efficiency of all but the highest type product relative the social welfare maximizing case ($\bar{e}_j < e_j^*$, $\forall j \in \{2,3,4,5\}$). The degree to which the efficiency is distorted downward reflects the trade-off to the monopolist of the profit impact of cutting costs on efficiency, and the risk of the customers substituting downward to lower efficiency products. On the other hand they provide the optimal level of efficiency to the high type ($\bar{e}_1 = e_1^*$). At the same time they charge more for all models than in the welfare maximizing case ($\bar{p}_j > p_j^*$, $\forall j \in \{1,2,3,4,5\}$). This price differential is higher for higher levels of efficiency.

I now turn to a scenario in which a minimum efficiency standard is imposed. This reproduces the same result as others who have discussed minimum efficiency standards in a market facing this type of price discrimination (e.g. Fischer, 2005). Assume in this simple example that the minimum efficiency standard requires that the monopolist only produce models with efficiency level greater than or equal to the socially optimal efficiency level for the lowest type of consumer (i.e. the minimum standard requires that $e_j \geq e_5^* \; \forall j \in \{1,2,3,4,5\}$). Note that this is a binding constraint for the monopolist, as absent any policy change, they would be choosing to produce the lowest type model with efficiency level $\bar{e}_5 < e_5^*$.

[24] I provide the proof of this for the three type case, which can easily be extended to more types, in Appendix B.2.

For simplicity I assume the standard is non-binding for all other efficiency levels such that $\bar{e}_j > e_5^*,\ \forall j \in \{1,2,3,4\}$. What happens to the monopolist's price strategy in the short run given the imposition of this standard? To answer this question I re-solve the monopolist's problem after introducing the constraint imposed by the standard, which we know will be binding for the lowest type of model. This new problem is presented in Equation 2.6.

$$
\begin{aligned}
\max_{p_1,p_2,\ldots,p_5,e_1,e_2,\ldots,e_5} \pi = \sum_{j=1}^{5} s_j \cdot (p_j - c(e_j)) \qquad (2.6)\\
s.t.\\
IR5 :&\theta^5 e_5 - p_5 = 0\\
ICi_{j+1} :&\theta^j e_j - p_j = \theta^j e_{j+1} - p_{j+1}, \forall j \in \{1,2,3,4\}\\
Standard :&e_5 = e_5^*
\end{aligned}
$$

The new monopoly solution of optimal price and efficiency levels given the standard, presented in slightly more detail than before, is shown in Equation System 2.7.

$$
\begin{aligned}
c'(e_5^S) =&c'(e_5^*) = \theta^5 \qquad (2.7)\\
c'\left(e_j^S\right) =&\theta^j - \frac{\sum_{k=1}^{j-1} s_k}{s_j}\left(\theta^{j-1} - \theta^j\right),\ \forall j \in \{2,3,4\}\\
c'(e_1^S) =&\theta^1\\
p_5^S =&\theta^5 e_5^*\\
p_4^S =&\theta^5 e_5^* + \theta^4\left(e_4^S - e_5^*\right)\\
p_3^S =&\theta^5 e_5^* + \theta^4\left(e_4^S - e_5^*\right) + \theta^3\left(e_3^S - e_4^S\right)\\
p_2^S =&\theta^5 e_5^* + \theta^4\left(e_4^S - e_5^*\right) + \theta^3\left(e_3^S - e_4^S\right) + \theta^2\left(e_2^S - e_3^S\right)\\
p_1^S =&\theta^5 e_5^* + \theta^4\left(e_4^S - e_5^*\right) + \theta^3\left(e_3^S - e_4^S\right) + \theta^2\left(e_2^S - e_3^S\right) + \theta^1\left(e_1^S - e_2^S\right)
\end{aligned}
$$

The result is that $\frac{\partial e_5}{\partial Standard} > 0,\ \frac{\partial e_j}{\partial Standard} = 0,\ \forall j \in \{1,2,3,4\},\ \frac{\partial p_5}{\partial Standard} > 0$, and $\frac{\partial p_j}{\partial Standard} < 0,\ \forall j \in \{1,2,3,4\}$ (note that this is because $\frac{\partial p_j}{\partial e_5} = (\theta_5 - \theta_4) < 0,\ \forall j \in \{1,2,3,4\}$). Now the lowest and highest types of customers are receiving the socially optimal level of efficiency given their preferences, while the middle types still have a lower level of efficiency relative to the socially optimal level. Although the low-type customer faces a price increase, it is just offset by the increase in their utility from improved efficiency, so they are no worse off from a utility perspective. All customer types above the lowest are made strictly better off, as they receive the same level of efficiency as before, but at lower prices.

In the case of a perfectly competitive market on the other hand, the efficiency-price schedule would already be socially optimal. Imposing a binding standard in that case would then be forcing the lowest efficiency level higher than the socially optimal level, $e_j \geq e^{standard} > e_5^*,\ \forall j \in \{1,2,3,4,5\}$. Therefore, if the market were perfectly competitive, and already operating at the optimal efficiency level, imposing a binding standard would result in $\frac{\partial p_5}{\partial Standard} > 0$ and $\frac{\partial p_j}{\partial Standard} = 0$, $\forall j \in \{1, 2, 3, 4\}$. However, if the increase in price of the lowest efficiency group resulted in type 5 consumers substituting to higher efficiency levels, then one might expect to see $\frac{\partial p_4}{\partial Standard} > 0$ as well.

2.2.2 Energy Star Standard Change

Here I extend the basic model to explore the implications of a change in only the Energy Star standard in the model with quality differentiated products. Houde (2012) explores the result of an increase in the Energy Star standard for refrigerators in 2008. Pulling somewhat from Houde (2012), assume consumers do not pay perfect attention to the efficiency level of the products they consider purchasing, and so e_j represents a composite of efficiency-relevant signals picked up by the consumer. One may be the true energy efficiency of the product, while another may be the Energy Star status of the product, etc. Therefore, a change in the Energy Star status of a product, even if the actual energy efficiency does not change, may result in consumers perceiving a change in the efficiency (e_j) of the product j.

Recall I assume a change in the Energy Star standard will only directly affect the three highest efficiency segment of the market, segments 1, 2 and 3. Look first at the case of products decertified from Energy Star as a result of the standard (segment 2). These products may be perceived as less energy efficient now that they no longer have the Energy Star label, even if the actual energy efficiency levels of the products have not changed, so consumers perceive e_2 going down. In the monopoly pricing strategy $\frac{\partial p_2}{\partial e_2} > 0$, therefore a decrease in e_2 will result in a price drop of decertified products in an imperfectly competitive market. In a perfectly competitive market a decertification from Energy Star might result in a negative demand shock, resulting in a drop in the price of segment 2 products as well.

Second, think about products that were not Energy Star certified either before or after the new standard, but are close substitutes to the segment 2 products (segment 3). These products now compete directly with products that were previously Energy Star certified, are of a higher average efficiency, and whose prices, while having just dropped, are likely still higher than p_3. These products are now closer substitutes with more expensive products, which means their prices may go up. However, they are of a lower average efficiency than products that are now closer substitutes and whose prices are dropping. This could mean type 3 consumers could substitute away from them, causing a negative demand shock and resulting in a drop in their price. Therefore, the prediction of the price impact to type 3 products is ambiguous, in either the imperfect competition or perfectly competitive case.

Finally, look at products that qualified for Energy Star both before and after the new standard (segment 1). You might think of two things happening to the type 1 products: first, consumers may perceive decertified products (segment 2) as less energy efficient than before, implying that consumers perceive e_2 decreasing; second, simultaneously the pool of products qualifying for Energy Star now consist of higher efficiency products on average. This means that consumers may perceive e_1 increasing. Therefore, the projected impact on the average price of this class of products is positive in the price-discrimination model, because $\frac{\partial p_1}{\partial e_1} > 0$ while $\frac{\partial p_1}{\partial e_2} < 0$. On the other hand, there is no expected direct effect on type 1 prices in the perfectly competitive model.

2.2.3 Oligopoly or Monopolistic Competition

In the previous two sections I outlined the price effect of either the minimum or the Energy Star standard changing in a monopolistic market. However, the clothes washer market in the United States is more oligopolistic or monopolistically competitive than monopolistic. There is a rich literature demonstrating that even when the monopoly assumption is relaxed to allow for a duopoly, oligopoly, or monopolistic competition, the unregulated case still results in an inefficient range of quality, with a depression of quality on the low-end below the socially optimal level, and prices still higher than socially optimal. In particular Katz (1984) discusses a case with multiple firms each selling a range of product quality, and with market power due to brand loyalty. This brand loyalty is modeled as a premium incurred by consumers of switching from the preferred brand. In this setting, there are higher margins on the high-end segments of the market, and more competition in the low-end of the market. This means sales of high-end products are more profitable, and it's therefore more important to capture and maintain the loyalty of those consumers on the high-end relative to the low-end. For this reason, quality on the low-end is depressed downwards to prevent high types from switching down. Therefore, quality is depressed on the low-end in the non-monopoly imperfect competition case, and price margins still increase with quality. Indeed De Meza and Ungern-Sternberg (1982) demonstrate it can even be the case that a monopolistically competitive market result in an even wider range of quality and even higher prices than in the monopoly case.

Additionally, others have demonstrated the theoretical impact of minimum quality standards on quality-differentiated markets that are not monopolistic, but rather oligopolistic or monopolistically competitive. In particular Ronnen (1991) develops a model of an industry in which two firms (later extended to some finite k number of firms in the market and an infinite number of potential entrants) face quality-dependent fixed costs and compete in quality and prices. In this model, the introduction of a minimum quality standard causes high quality sellers to increase quality to alleviate price competition induced by the collapsing of the quality range on the low end. However, the assumption that $c''(e) > 0$ assures high quality producers raise quality less than the increase in quality on the low end induced by the minimum quality standard. This means price competition is intensified regardless of attempts by high-end firms to alleviate it, so in the end, prices (controlling for quality level) still drop. Crampes and Hollander (1995) extend the model developed by Ronnen (1991) by allowing the quality costs to be variable instead of fixed. They find the same qualitative results as did Ronnen (1991), but while Ronnen (1991) showed that consumers necessarily gain from a minimum quality standard, Crampes and Hollander (1995) show that consumer welfare increases only if the high quality firm does not respond by raising quality too drastically.

Therefore, predictions for an oligopolistic or monopolistically competitive market are qualitatively consistent with the monopoly case, implying that using the predictions from the monopoly model is a reasonable proxy for the non-monopoly imperfect competition setting.

2.2.4 Testable Price Predictions of a Combined Increase in the Minimum and Energy Star Standards

In this section I take the results presented in Sections 2.2.1 and 2.2.2, which provided predictions of the affect on market prices of either the minimum or Energy Star standard changing separately, and combine the results to determine the price effect predictions when both these standards change simultaneously. Table 2.2 summarizes the price predictions of a simultaneous change in the minimum and Energy Star standard in an imperfectly competitive market, while Table 2.3 outlines the corresponding predictions under perfect competition.

In a market with five consumer types and imperfect competition, Table 2.2 shows that a combined increase in both the minimum and Energy Star standards should result in the aggregate effect of a price decrease for models decertified from Energy Star (segment 2), and a price decrease for models that are close substitutes to the those directly impacted by the minimum standard (segment 4). The price of the market segment for which the minimum standard is binding (segment 5) is predicted to see a price increase in nominal terms, although importantly it would be a decrease in efficiency-adjusted terms. The predictions for the market segments 1 and 3 are unclear.

In a perfectly competitive market on the other hand, as shown in Table 2.3, a combined minimum and Energy Star standard increase should result in no price change for the highest efficiency segment (1), a price decrease for models decertified from Energy Star (segment 2) and an ambiguous effect on segment 3 products. The primary difference between the predictions from the perfect competition model and the price discrimination model is the effect of the standard on the mid-low range of efficiency (here described as segment 4). The lowest segment for which the new minimum standard is binding (segment 5) should see an unambiguous increase in price under perfect competition. Additionally, while in the imperfect competition case the effect on the price of market segment 4 was an unambiguous price decrease, the prediction under perfect competition should be either that there is no price change for these products, which would be the result if type 5 consumers simply exit the market when p_5 increases, or that some marginal consumers of type 5 might respond to the price increase of the lowest market segment products by substituting to the next highest efficiency level, now that the price differential between these two market segments is less. This would create a positive demand shock in market segment 4, resulting in a price increase. Note that the same could be the case cascading upward all the way to segment 1.

Table 2.2: Imperfect Competition Price Predictions Following Increase in Minimum & Energy Star Standards

Market Segment	Description of Market Segment	Price Prediction: Minimum Std	Price Prediction: Energy Star Std	Price Prediction: Combined
1	Energy Star → Energy Star	↓	↑	Ambiguous
2	Energy Star → Decertified	↓	↓	↓
3	Close substitutes to decertified	↓	Ambiguous	Ambiguous
4	Close substitutes to segment 5	↓	-	↓
5	Minimum standard binding	↑*	-	↑*

* While the model predicts an increase in prices for this segment in nominal terms, prices actually drop in efficiency-adjusted terms.

Note: Predictions of the price effects of a simultaneous increase in both the minimum and Energy Star efficiency standard under imperfect competition across the energy efficiency spectrum of the market.

Table 2.3: Perfect Competition Price Predictions Following Increase in Minimum & Energy Star Standards

Market Segment	Description of Market Segment	Price Prediction: Minimum Std	Price Prediction: Energy Star Std	Price Prediction: Combined
1	Energy Star → Energy Star	-	-	-
2	Energy Star → Decertified	-	↓	↓
3	Close substitutes to decertified	-	Ambiguous	Ambiguous
4	Close substitutes to segment 5	↑*	-	↑
5	Minimum standard binding	↑	-	↑

* This would be the case if we assume that some marginal consumers of type 5 might respond to the increase in the price of the lowest market segment of products by shifting to substitutes with a higher level of efficiency, now that the price differential between these two market segments are less. This would create a positive demand shock in market segment 4, resulting in a price increase in that market segment.

Note: Predictions of the price effects of a simultaneous increase in both the minimum and Energy Star efficiency standard under perfect competition across the energy efficiency spectrum of the market.

2.2.5 Other Model Predictions

Tables 2.2 and 2.3 outline the primary price predictions differentiating a perfectly competitive market reaction from a market with imperfect competition and price discrimination, namely prices in the mid-low range of the market should increase under perfect competition and decrease under price discrimination. In this section I outline two additional testable predictions in this model. First, Ronnen (1991) and Crampes and Hollander (1995) derive that following a new minimum quality standard, imperfectly competitive producers have an incentive to expand quality upwards to increase the spread of quality in the market again following the new standard. They do this to alleviate the increased price competition between market segments imposed by the quality distribution collapse following the new standard. Therefore, a second prediction is that there will be an increase in innovation and model proliferation in the highest efficiency range of the market following the new standard, as firms spread the efficiency distribution upwards in their attempt to re-establish a new optimal price-efficiency schedule.

Finally, the predictions of the price effects of a new minimum standard in the imperfectly competitive model are contingent on the supposition that firms have been price-discriminating and charging increasingly positive margins for higher levels of efficiency. If, however, the market has been otherwise forced to increase efficiency and/or reduce margins already, then changing the minimum efficiency standard should result in less of a downward price effect. This is relevant in this setting as the clothes washer market faced a change in the minimum and Energy Star standards in 2004, and then again shortly thereafter in 2007. The model would therefore predict that the effects in line with price-discrimination should be most pronounced at the time of the 2004 standard change. This change would result in a depression of price margins and the firms may not have been able to re-establish an optimal pricing strategy fully by the time of the 2007 standard change. Therefore in 2007 one should expect to see less of the price effects predicted by the price discrimination model compared to 2004.

2.3 Data

I use POS data for clothes washers, dryers and room air conditioners (room ACs) from NPD Group.[25] These data are acquired from an incomplete set of retailers nationwide (a list of participating retailers can be found in Appendix B.3). The data are aggregated to the national level and consist of monthly total revenue and total quantity sold observations by model number. The data also include information on some model characteristics, though for a subset of observations.

The NPD data for clothes washers were matched with energy usage data, measured in kilowatt-hours per year (kWh/year), by model number and year from the Federal Trade Commission (FTC) appliance energy database.

In order to control for changes in macroeconomic shocks to the appliance market, and to control for changes to the data mix of the NPD data, I use both dryers and room ACs as counterfactual groups.[26] Neither dryers nor room ACs had any adoption or effective

[25] NPD is not an acronym, but rather the name of the company: The NPD Group, Inc., The NPD Group/NPD Houseworld. Port Washington, NY.

[26] Some retailers did enter or exit the data at different times in the series. NPD attempts to maintain consistency within the data over time, and I was assured by NPD that the large retailers do not change over the study period. Data are available for refrigerators and dishwashers as well. Unfortunately, dishwashers experienced a change in the test procedure used to determine compliance with standards right before January 2004, which resulted in price volatility for this product at that time. Additionally the Energy Star standard for dishwashers changed January 1st, 2007, and changed for refrigerators on January 1st, 2004. This makes these appliances unusable as counterfactual groups.

dates for either minimum efficiency or Energy Star standard changes over the range of the study period. There are issues with using either of these appliances as counterfactuals. First, room ACs, while arguably a relatively independent product from clothes washers, did experience more general price volatility and were more prone to seasonal price variability. Second, clothes washers and dryers are not independent markets, and so using dryers as a comparison to measure the market impacts of the standard for clothes washers is likely to be more conservative than using another, less linked, product. This is because dryers and washers are likely compliments, and therefore their prices and sales should be positively correlated.

The NPD data, while extensive in some ways, are imperfect in others. In particular, a large subset of the model numbers are masked to ensure anonymity of retailers. These models cannot be matched to the FTC energy usage data, and therefore must be omitted from my analysis (40% of the observations in the focus period of this analysis must be dropped for this reason). Of the models that do have fully detailed model numbers, not all are included in the FTC energy usage database, and must therefore be omitted as well (82% of the data with fully detailed model numbers for clothes washers in the focus period of this analysis are successfully matched to FTC data). In order to maintain comparability between clothes washers and the counterfactual appliance groups, masked model numbers were also dropped from the dryer and room AC data.[27]

As mentioned in Section 2.1, the energy measures used to determine the compliance of washer models with minimum and Energy Star standards are the EF, MEF and WF. Unfortunately, data on these efficiency measures are not available for the majority of the models in the NPD data during this period. It is therefore impossible to identify which models meet either the minimum standard or the Energy Star standard specifically at each time period in the sample. The available energy efficiency metric is the FTC measure of kWh/year used by each washer model in each year. This measure does not correspond directly to any of the DOE efficiency measures (EF, MEF or WF) used to set the standards. However, the FTC kWh/year measure is an important indicator of energy consumption, particularly from the perspective of the consumer purchase decision; it is the FTC measure that is required to be posted on products at the retail outlet to inform consumers about the energy use of their potential purchases. In this study therefore, models are stratified based on this FTC metric of energy use as a proxy for determining the direct impact of the change in standards across the market. This will be discussed in more detail in Section 2.4.2.

There are 699 unique clothes washer models, 820 unique dryer models, and 595 unique room AC models used in the analysis. An individual appliance model number in these data uniquely identifies a particular design. Therefore, any change in characteristics of an individual model over time would be a small internal change that would not otherwise affect the appearance of the product. Even small internal changes may result in a change in the

[27]Appendix B.4 provides figures showing the comparison of price (as represented by average revenue from the NPD data) for those models included in the full analysis, and those models omitted. Generally, models used in the analysis tended to be slightly more expensive than those omitted for all three appliances, though more so for clothes washers and dryers. In Appendix B.6 results from a robustness check – wherein none of the data are omitted – analogous to the estimation presented in Section 2.4.1 are reported. This is done in order to demonstrate that the average effects of the new standards on prices were not driven only by the subset of the data used in the primary analysis.

washer model number, depending. Of the clothes washer models in the data that do have a set of descriptive characteristics, none of the observable characteristics of a given washer model change over time except one: the FTC energy usage measure. Even in this case it only changes slightly for a handful of models. Therefore, controlling for model-specific fixed effects will control for more or less all relevant characteristics of the models from a consumer perspective. If a major characteristic changes, then this results in a new unique model number.

Table 2.4 shows summary statistics for the data used in the full analysis. The changes to clothes washer standards are indicated by the double vertical lines between 2003 and 2004, and between 2006 and 2007 in the table. The average deflated prices of clothes washers and dryers have risen on average between 2003 and 2007; washers cost \$626 in 2009 dollars on average in 2003, and that increased to \$690 in 2007. Similarly dryers cost \$465 in 2009 dollars on average in 2003 increasing to \$590 in 2007. On the other hand, the average prices of room ACs went down slightly over this time period, costing \$392 on average in 2009 dollars in 2003 and \$366 on average in 2009 dollars in 2007. The efficiency of clothes washers, as measured by the average FTC kWh/year usage of these products, has steadily improved over this period as well, averaging 714 kWh/year usage in 2003 and improving to a usage of only 312 kWh/year on average in 2007. Additionally, the prevalence of front-loading washer models has steadily increased over time, making up 15% of observations in 2003 and increasing to 46% of observations in 2007. Finally, the standards for clothes washers are different for compact models versus standard-sized models. However, of observations in the data for which the capacity variable is available, only 0.95% are for compact models. Therefore, the vast majority of models in the data are standard-class models (capacity greater than 1.6 cubic feet).

Table 2.4: Summary Statistics

Clothes Washers

	2003		2004		2005		2006		2007	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Price	626.00	374.96	680.51	408.93	712.64	396.05	703.92	377.71	690.23	335.79
FTC kWh/year	714.12	275.41	446.88	192.77	392.95	161.06	367.97	154.12	311.63	133.06
Share TL	0.85	0.36	0.75	0.43	0.68	0.47	0.64	0.48	0.54	0.50
Percent of Clothes Washers that are Compact (<1.6 cubic feet) in data: 0.95%										

Counterfactual Appliances

	2003		2004		2005		2006		2007	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Dryer Price	465.18	204.52	519.84	265.89	537.25	248.75	548.57	249.12	589.73	257.33
Room AC Price	391.78	219.08	335.78	210.21	334.32	210.13	359.80	211.67	366.46	217.84

Note: Summary statistics of NPD data for clothes washers, dryers, and room ACs. All prices are calculated as average revenue (total revenue divided by total units sold in a given month), and are deflated using the CPI with a base period of December 2009. "Share TL" is the share of observations consisting of sales of top-loading washers as opposed to front-loading washers. Double vertical lines indicate when the minimum and energy star standards changed for clothes washers.

2.4 Results

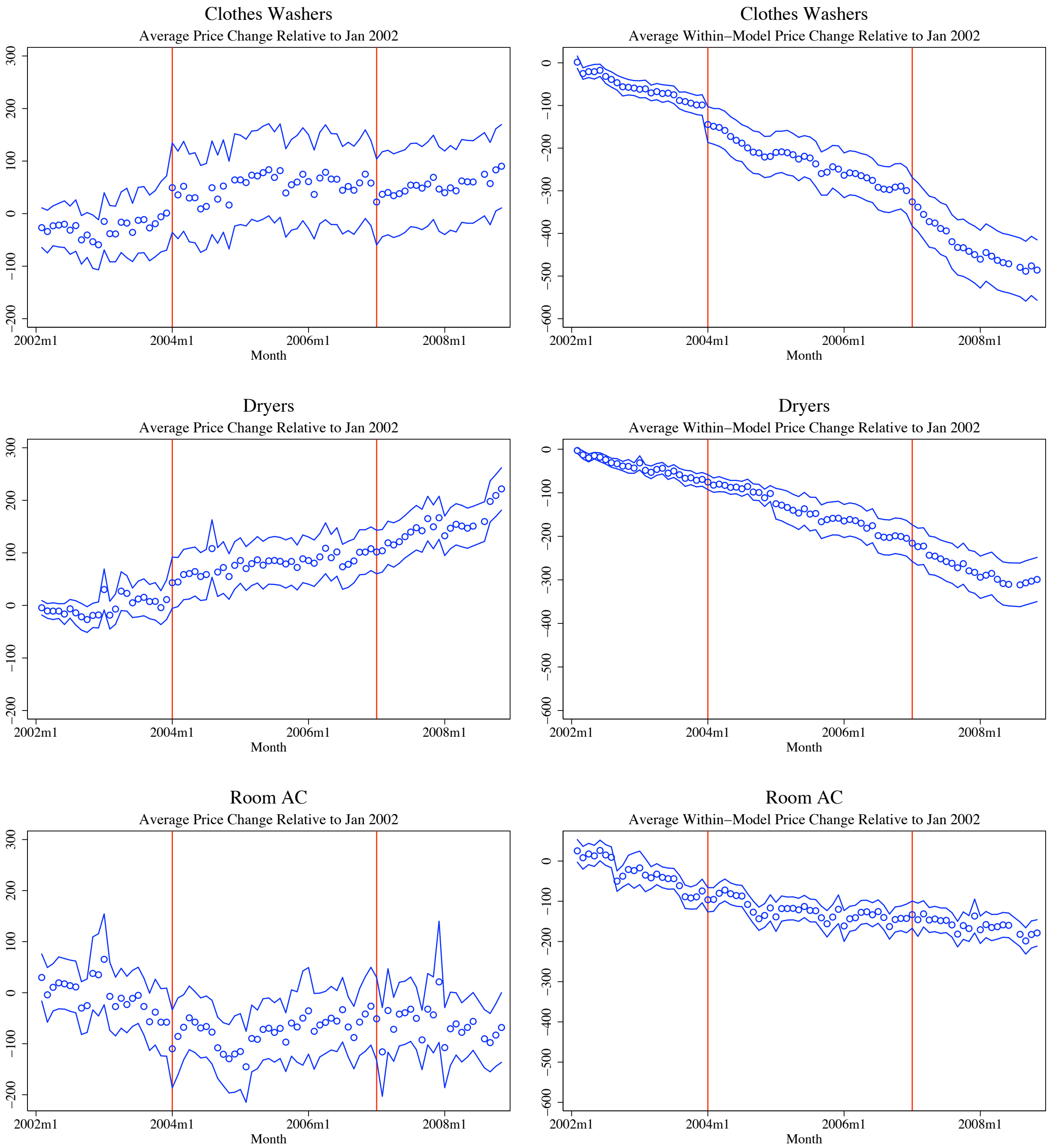
Before exploring the empirical results that address the price change predictions in different efficiency-based market segments, I do a baseline analysis showing the effect of the standard changes on the average clothes washer prices in 2004 and 2007. These results are presented in Section 2.4.1. I then progress to a deeper exploration of the price changes, allowing a differentiated price effects across efficiency categorizations. This analysis is presented in Section 2.4.2. In both cases, average and efficiency-differentiated results, I use four estimation strategies to capture the scope of price changes. I estimate four price changes at the time of the new standard: first, the market average price change not controlling for any model characteristics; second, the average within-model price change by controlling for model-specific fixed effects; third, the market average price change again, but rather than looking at first-differences, I use a difference-in-difference (DD) model using dryers and room ACs as counterfactual appliance groups, and finally, the average within-model price change again, but using the DD model and counterfactual groups as well.

Intuitively, estimating the effect of the standard with and without fixed effects captures a full picture of the price changes concurrent with the implementation of the new standard; the firms in this market may react to the standard in one, or both, of two possible ways: they can change the mix of models in the market, and they can change the price-efficiency schedule of existing models in the market. The analysis with no fixed effects captures the average market price change both at the intrinsic (price change of existing models) and extrinsic (change in model mix) margins. This analysis answers the question, “If a consumer walked into a store right after the new standard, what is the change in the price distribution across all models they would face relative to if they walked into the store right before the standard?” The analysis with fixed effects, on the other hand, controls for all time-invariant characteristics of a given model, which ends up being more or less all relevant model characteristics other than prices and standard compliance. Therefore, it will not capture any price changes due to a change in model mix, but will isolate the portion of the average price change that is due to that of existing models. This analysis answers the question, “If a consumer walked into a store right after the new standard, what is the change in the price of model X they would face relative to if they walked into the store right before the standard?”

Figure 2.3 shows the clothes washer, dryer and room AC price trends over the study period. The left-hand column shows the overall market average price trends while the right-hand column shows the within-model price trends. As can be seen in the left-hand panels of Figure 2.3, the average dryer price appears to have risen more quickly than that of clothes washers, while the average room AC price does not appear to have risen at all over this period. I account for this by allowing overall price trends to vary by appliance.

The average clothes washer price at the 2004 standard change appears to bump up slightly, but so does the dryer price at that point, so it is unclear whether this might be in part due to some macroeconomic jump, or due to the change in data mix. On the other hand the average market room AC price appears to dip down slightly at the time of the 2004 standard change, but only for a month or two. At the time of the standard change in 2007 it appears that average clothes washer prices dipped down notably, but there was no discernible change for either dryers or room ACs.

Figure 2.3: Market Average and Within-Model Price Trends



Note: Market-average (left column) and within-model (right column) price trends for clothes washers (top row), dryers (middle row) and room ACs (bottom row) between 2002 and 2008. All prices are real (deflated using the CPI with December 2009 base-period), and are shown relative to the average price level in January 2002. The solid vertical lines show when the standard changed for clothes washers (January 2004 and January 2007). The solid lines indicate 95% confidence intervals.

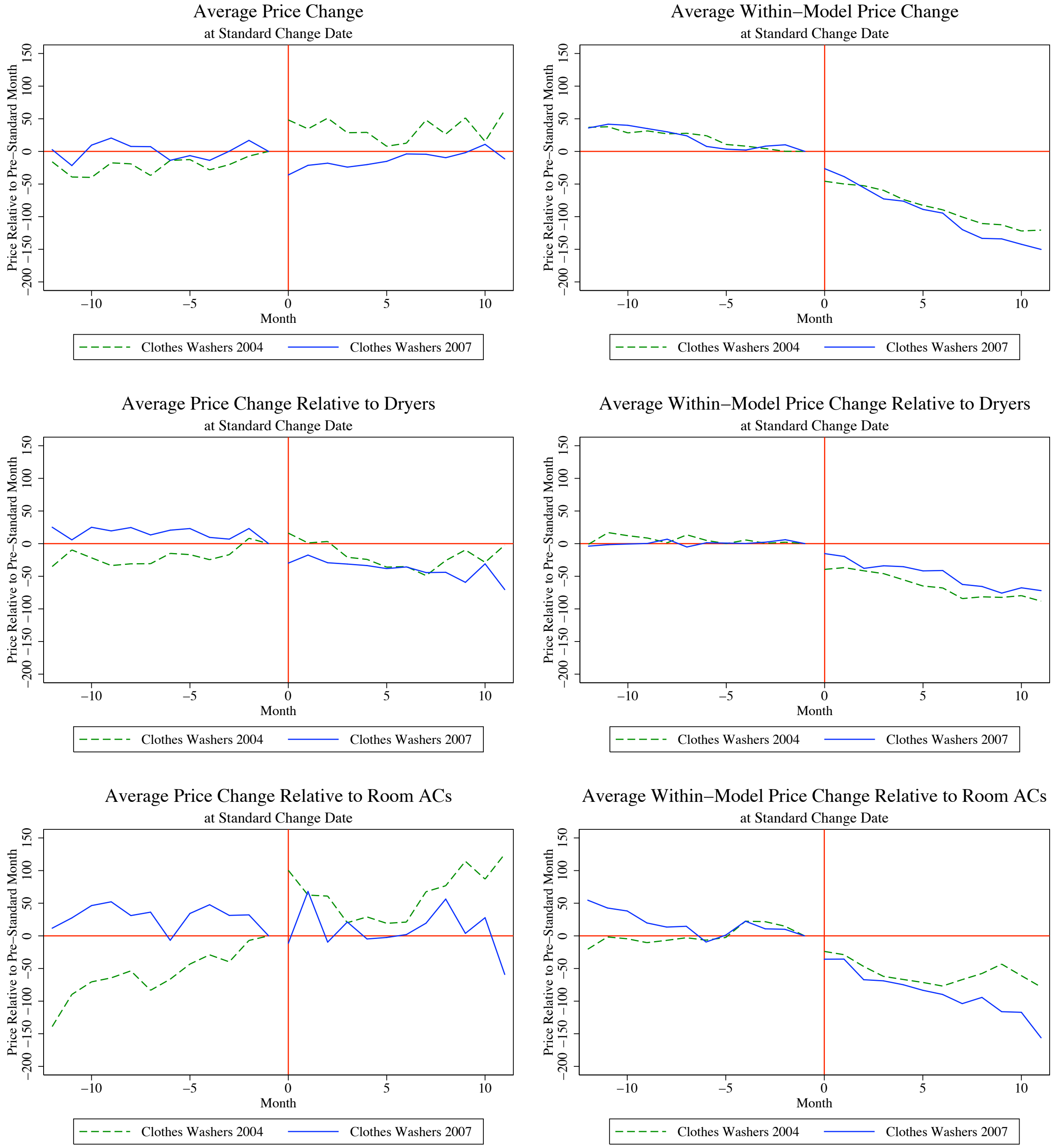
Turning now to the right-hand column of Figure 2.3, the within-model prices drop steadily over this time period, though less so for room ACs than clothes washers or dryers. Firms with market power have an incentive to provide new efficient products at a high price early, and then reduce the price over time, as this allows them to price-discriminate between high and low-type consumers intertemporally. Consumers with a higher valuation for efficiency will purchase the products early, at a higher price, and then consumers with a lower valuation for efficiency will wait to purchase the product until the price drops (Landsberger and Meilijson, 1985; Kühn, 1998; Koh, 2006). This could be a factor in the downward trend of within-model deflated prices. Another factor might be "learning" in the production process, suggesting that production costs drop over time as suppliers fully optimize production of a new technology. Aside from the overall average within-model price drop over this period, note the visible price drop, downward trend-break, or both, at both standard change dates for clothes washers but not for dryers or room ACs. The next section explores these price effects more rigorously.

2.4.1 Average Price Effect of Standard Change

In this section I estimate the short-run price effect at the time of the combined minimum and Energy Star standard changes, without differentiating across efficiency levels. Figure 2.4 shows the price changes at both instances of the standard changing. The standard changes when time (measured in months) is equal to zero. The price change at the standard is shown relative to the month just preceding the standard change. The top two panels of Figure 2.4 show the first-differences price change within clothes washers (i.e. without using a counterfactual). The middle two panels of Figure 2.4 show the price change relative to dryers as a counterfactual, and the bottom two panels do the same using room ACs as the counterfactual. The left-hand panels of Figure 2.4 show the average market price change, without controlling for anything about the specific models. The right-hand panels of Figure 2.4 show the within-model price changes by including model-specific fixed effects.

In all cases, and also in the regression results presented below, I limit the analysis to the time frame immediately around the standard, specifically one year prior to the standard change and one year after. I do this because there are several different policy changes affecting clothes washers at different points over the period for which I have data. Also, in 2008 and beyond, the prices off all appliances start becoming more volatile, possibly due to economic volatility. I therefore choose to focus on the short-run effect of the change in standard to isolate the analysis from these other factors. This is also the most relevant lens for testing the imperfect competition price-discrimination model predictions presented in Section 2.2.

Figure 2.4: Price Change at Standard Change Dates



Note: The change in market-average (left column) and within-model (right column) price relative to the month just preceding each standard. All prices are real (deflated using the CPI with December 2009 base-period). The change in standard went into effect at month 0 in all cases. This price change is shown within clothes washers only (top row), relative to dryers (middle row), and relative to room ACs (bottom row).

As can be see in Figure 2.4, the average effect on prices at the time of the new standard, particularly within-model, is downward. If the concurrent change in either counterfactual price is not used as a reference, then it appears that prices increased for clothes washers as a result of the 2004 standard. However, after controlling for the concurrent dryer price change the upward change in clothes washer prices is dampened. The positive price effect of the 2004 standard when depicted relative to room ACs as the counterfactual group is still present, however there is a lot of noise and while prices jump up for the first two or three months, they drop down again quickly thereafter. While results for the average price effect in the left-hand panels of Figure 2.4 appear to be more ambiguous, the within-model price changes appear to consist of an immediate downward discontinuous drop in prices just at the implementation date of both new standards. Additionally, there appears to be a downward trend-break in within-model prices at the time of both standards.

In order to quantify the effects shown graphically in Figure 2.4, I conduct a series of OLS regressions, the results of which are presented in Tables 2.5 and 2.6. The dependent variable in all cases is price, which has been deflated using the CPI with December 2009 as a base period. To be explicit, the full estimating equation is presented in Equation 2.8, where p_{it} is deflated price at time t of model i. The variable T_i is a dummy variable equal to one if the observation is for an appliance affected by the standard (clothes washers) and equal to zero otherwise (dryers or room ACs). The term $Trend_t$ is a linear time trend; $Standard_t$ is a dummy variable that turns on at the time the new standard takes effect, and $Trend_t * Standard_t$ is a term that is equal to zero for all observations up until the time of the standard and begins increasing by one unit each month following the standard. In the regressions with fixed effects the term μT_i is omitted, in the regressions without fixed effects γ_i is omitted, and for regressions with no counterfactual group $\beta_1 = \beta_2 = \beta_3 = 0$ and μT_i is omitted.

The coefficients of interest are the coefficients on $T_i * Standard_t$ and $T_i * Standard_t * Trend_t$. The coefficient on $T_i * Standard_t$ is interpreted as the discontinuous level change, in dollars, of the price at the time of the new standard, and the coefficient on $T_i * Trend_t * Standard_t$ is interpreted as the change in the average incremental amount, in dollars, by which prices rise or fall each month following the standard relative to before the standard. In the regressions with a counterfactual, the effects are interpreted relative to the counterfactual.

$$\begin{aligned} p_{it} = &\alpha + \beta_1 Trend_t + \beta_2 Standard_t + \beta_3 Standard_t \cdot Trend_t + \mu T_i \\ &+ \psi T_i \cdot Trend_t + \delta T_i \cdot Standard_t + \phi T_i \cdot Standard_t \cdot Trend_t + \gamma_i + \varepsilon_{it} \end{aligned} \tag{2.8}$$

Table 2.5 shows the results with no fixed effects and Table 2.6 shows the results with fixed effects. In both Table 2.5 and 2.6 I present six sets of regression results. Columns (1) and (4) in both tables present the results of the first-difference regressions that do not include a counterfactual; Columns (2) and (5) in both tables present the results of the DD regressions including dryers as the counterfactual, and finally Columns (3) and (6) in both tables present the results of the DD regressions including room ACs as the counterfactual. Columns (1), (2) and (3) in both tables look at the effect of the 2004 change in standard. Columns (4), (5) and (6) look at the effect of the 2007 change in standard.

Table 2.5: Average Price Effect at New Standard Effective Dates

	2004 Standard Change			2007 Standard Change		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var: Price	No Controls	Dryers as Controls	Room AC as Controls	No Controls	Dryers as Controls	Room AC as Controls
T		146.7***	185.8***		161.9***	345.9***
		(34.94)	(36.50)		(35.93)	(35.96)
Trend		-0.418	-6.444***		1.219	0.434
		(1.506)	(2.135)		(1.376)	(2.171)
Standard		43.47**	18.30		1.271	-8.558
		(18.11)	(18.15)		(10.46)	(22.03)
Trend * Standard		2.877	0.295		4.621**	1.850
		(2.447)	(2.983)		(2.176)	(3.586)
T * Trend	2.043	2.461	8.487**	0.103	-1.116	-0.331
	(2.548)	(2.959)	(3.323)	(2.027)	(2.449)	(2.970)
T * Standard	40.83	-2.635	22.54	-29.49*	-30.76	-20.93
	(35.64)	(39.96)	(39.98)	(16.66)	(19.66)	(27.62)
T * Trend * Standard	-1.872	-4.749	-2.167	2.651	-1.970	0.801
	(4.010)	(4.696)	(4.997)	(2.885)	(3.612)	(4.602)
Constant	614.2***	467.5***	428.4***	703.3***	541.4***	357.4***
	(31.96)	(14.15)	(17.65)	(31.41)	(17.48)	(17.52)
Model Fixed Effects	N	N	N	N	N	N
Observations	3,637	7,283	6,422	4,793	10,655	7,129
R-squared	0.005	0.068	0.165	0.001	0.044	0.198

Standard errors in parentheses clustered by model number

*** p<0.01, ** p<0.05, * p<0.1

Note: Results for regressions estimating the concurrent effect of the new standard (either 2004 or 2007) on the market average price of clothes washers. Columns (1) and (4) only include clothes washer models, while Columns (2) and (5) look at the effect relative to dryers, and Columns (3) and (6) look at the effect relative to room ACs. No controls or fixed effects are included.

Looking first the results presented in Table 2.5, there were almost no statistically significant changes in the market average price of clothes washers at either standard. We see from these results that there was a slight increase in the market average price of washers at the time of the 2004 standard, though it is not statistically significant either in the first-differences specification, nor relative to dryers or room ACs. There was a slight price drop on average for clothes washers at the time of the 2007 standard, though it is only marginally significant in only one specification. We see confirmation of what is clear from Figures 2.3 and 2.4, that prices of room ACs were trending down relative to prices of clothes washers around the time of the 2004 standard, but there are no significant trend-breaks at the time of the standard changes for clothes washers in any specification. These results indicate that the distribution of prices faced by the consumer did not shift significantly at the time of either standard. If the standard resulted in cheaper, less-efficient models simply being dropped from the market with no additional price or menu adjustment, we should see an increase in prices on average at the time of the standard. This apparently was not the case.

Table 2.6: Within-Model Price Effect at New Standard Effective Dates

	2004 Standard Change			2007 Standard Change		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var: Price	No Controls	Dryers as Controls	Room AC as Controls	No Controls	Dryers as Controls	Room AC as Controls
Trend		-3.600***	-7.083***		-5.159***	-2.328***
		(0.548)	(0.905)		(0.648)	(0.795)
Standard		-1.683	36.10***		-2.954	14.50*
		(4.290)	(7.230)		(4.202)	(7.629)
Trend * Standard		0.413	0.762		-2.438**	-0.744
		(0.974)	(1.171)		(0.984)	(1.306)
T * Trend	-4.342***	-0.743	2.741**	-5.754***	-0.595	-3.426***
	(0.815)	(0.976)	(1.220)	(0.835)	(1.056)	(1.158)
T * Standard	-36.58***	-34.90***	-72.68***	-13.23**	-10.28	-27.73***
	(11.16)	(11.87)	(13.34)	(6.383)	(7.639)	(9.981)
T * Trend * Standard	-3.054***	-3.468**	-3.816**	-7.079***	-4.641***	-6.335***
	(1.098)	(1.461)	(1.609)	(1.371)	(1.687)	(1.901)
Constant	739.1***	634.3***	603.6***	799.2***	714.6***	663.0***
	(11.36)	(5.985)	(6.907)	(9.330)	(5.389)	(6.549)
Model Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	3,637	7,283	6,422	4,793	10,655	7,129
R-Squared	0.235	0.209	0.223	0.319	0.300	0.293
Number of Models	418	736	790	431	959	751

Standard errors in parentheses clustered by model number

*** p<0.01, ** p<0.05, * p<0.1

Note: Results for regressions estimating the concurrent effect of the new standard (either 2004 or 2007) on the market average within-model price of clothes washers. Columns (1) and (4) only include clothes washer models, while Columns (2) and (5) look at the effect relative to dryers, and Columns (3) and (6) look at the effect relative to room ACs. Model-specific fixed effects are included in all specifications.

I now turn to the results of the regressions including fixed effects, presented in Table 2.6. In all but one specification there is both a statistically significant discontinuous drop in within-model prices at the time of the standard, and a statistically significant downward trend-break in the rate at which within-model prices of clothes washers are dropping over time starting at the time of each new standard. In particular, within-model prices of washers dropped \$36.58 on average at the time of the 2004 standard; this drop was \$34.90 relative to the concurrent change in within-model dryer prices, and \$72.68 relative to the concurrent change in within-model room AC prices. At the time of the 2007 standard change the within-model average price drop was less: \$13.23 (not significant relative to dryers and \$27.73 relative to room ACs). At the time of the 2004 standard change, within-model clothes washer prices began dropping between \$3 and \$4 more quickly each month after the standard relative to before in all specifications. This downward trend-break was slightly larger in magnitude at the time of the 2007 standard (between \$4 and \$7 per month).

Overall, it is clear these standards appeared to be associated with relatively strong downward pressure on within-model prices, and no evidence of an increase in overall average prices.

It would be difficult to claim, given these results, that tightening the standards resulted in an increase in appliance prices on average during these two standard changes. This would be puzzling if we assumed that the market for appliances was perfectly competitive. I now turn to an analysis of these effects looking at the heterogeneity across efficiency levels in the market. These results will begin to speak directly to the predictions from the price discrimination model presented in Section 2.2.

2.4.2 Testing Model Prediction: Effects on Prices by Efficiency Level

In this section I address the testable predictions of price changes derived in Section 2.2.4 directly. To this end I break the appliance markets into five categories based on the FTC kWh/year energy use measure and explore the differential effects of the new standards across these efficiency groups. Given the framing of the predictions from the model presented in Section 2.2, it would be ideal if I were able to identify which models were Energy Star qualified and/or met the minimum standard at each time period. Unfortunately, the energy use data currently available, as mentioned above, is the FTC's kWh/year consumption measure. This is not the same energy use measure used to determine the cut-offs for the minimum and Energy Star standards. For this reason, I must approximate the five market segments defined in the model as best I can. To this end, I categorize all the models using quintile cut-offs of energy consumption based on the FTC kWh/year measure right around each standard. In order to provide the most consistent categorization across time, I do the following: first, I calculate the quintile cut-offs (20th, 40th, 60th, and 80th percentiles) of energy use across the sample in the year just prior to the standard for each standard separately. I then categorize all models with observations of their FTC model number[28] in that year prior to the standard, based on these cut-offs (i.e. a FTC model number whose energy consumption is less than the 20th percentile is placed in Group 1, a FTC model number with energy consumption between the 20th and 40th percentile cut-offs is placed in Group 2, etc). Then, if there are any FTC model numbers that do not appear in the data until after the new standard, I calculate quintile cut-offs for the year just following the standard for each standard separately, and categorize the models that have not already been categorized. Therefore, in the end, each model with observations within the two year window around each standard is given a unique group categorization (Group 1, 2, 3, 4 or 5). The categorization is primarily based off the pre-standard energy use distribution, but is filled in with a categorization based off the post-standard energy use distribution only for models that did not appear in the data

[28]A model number from the FTC database generally matches to more than one model number in the NPD data. I categorize the models into efficiency groups based on the FTC model number, rather than the NPD one. This is because, particularly in 2004, a large number of models exited the market the month before the standard, and re-entered the market the month following the standard with the exact same model number except for one or two characters. These pairs of models are matched to the same FTC model number, indicating that the models are more or less identical in terms of consumer features, but perhaps had internal changes to make them more efficient. Therefore if a model is adapted in this way, both occurrences of this model are categorized into the same efficiency group, as what I'm interested in is looking at changes to the efficiency group as determined before the standard at the time the standard is imposed. This categorization method accomplishes this.

prior to the standard (9.34% of data used in the estimation were filled in with post-standard categorizations).

After categorizing each model into one of the efficiency groups (1, 2, 3, 4 or 5, where Group 1 is the highest efficiency group and Group 5 is the lowest efficiency group), I run a series of regressions that mirror those I presented in Section 2.4.1. In particular, the dependent variable in all cases is still the deflated price. In all regressions I include a linear overall time trend, which I allow to differ across efficiency market segment ($Group_{ji} * Trend_t$), where $Group_{ji}$ is a dummy variable equal to one if model i is categorized into Group j, $\forall j \in \{1,2,3,4,5\}$, and zero otherwise. Now, instead of estimating the average effect of the standard, I estimate the effect of the standard differentiated across the five efficiency groups, captured by the variable $Group_{ji} * Standard_t$, where $Standard_t$ is still a dummy variable equal to zero prior to the standard, and equal to one for all observations thereafter. The variable $Trend_t * Standard_t$ is still equal to zero for all observations up until the time of the standard and begins increasing by one unit each month following the standard, however I now look at this change-in-trend term differentiated across groups, so the relevant variable is now $Group_{ji} * Trend_t * Standard_t$. When I include a counterfactual group, I include variables $Trend_t$, $Standard_t$ and $Trend_t * Standard_t$ to capture the average change in counterfactual prices around the standard. Finally, in the regressions without fixed effects I include the variables $Group_{ji}$, $\forall j \in \{1,2,3,4,5\}$. The coefficients of interest are the coefficients on $Group_{ji} * Standard_t$ and $Group_{ji} * Trend_t * Standard_t$. Note that while I still use a counterfactual, dryers and room ACs are not categorized into any efficiency groups, so the effect on the prices of a given efficiency group when interpreted relative to a counterfactual should be interpreted as relative to the average change in counterfactual prices across the whole counterfactual market. Once again to be explicit, the full estimating equation is presented in Equation 2.9, where p_{it} is still deflated price at time t of model i. In the regressions with fixed effects the terms $\mu_j Group_{ji}$ are omitted; in the regressions without fixed effects γ_i is omitted, and for regressions with no counterfactual group $\beta_1 = \beta_2 = \beta_3 = 0$ and $\mu_3 Group_{3i}$ is omitted. The results of the regressions without fixed effects are presented in Table 2.7 and the results of the regressions with fixed effects are presented in Table 2.8.

$$\begin{aligned} p_{it} =& \alpha + \beta_1 Trend_t + \beta_2 Standard_t + \beta_3 Standard_t \cdot Trend_t + \sum_{j=1}^{5} \mu_j Group_{ji} \\ &+ \sum_{j=1}^{5} \psi_j Group_{ji} \cdot Trend_t + \sum_{j=1}^{5} \delta_j Group_{ji} \cdot Standard_t + \sum_{j=1}^{5} \phi_j Group_{ji} \cdot Standard_t \cdot Trend_t + \gamma_i + \varepsilon_{it} \end{aligned} \tag{2.9}$$

Table 2.7: Average Price Effects at New Standard Effective Dates: Efficiency-Level Specific Results

	2004 Standard Change			2007 Standard Change		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var: Price	No Controls	Dryers as Controls	Room AC as Controls	No Controls	Dryers as Controls	Room AC as Controls
Trend		737.5***	776.5***		537.3***	721.3***
		(112.7)	(113.2)		(72.58)	(72.64)
Standard		150.6*	189.6**		489.6***	673.6***
		(88.09)	(88.74)		(74.24)	(74.31)
Trend * Standard		93.38	132.4*		74.98	259.0***
		(67.75)	(68.58)		(54.29)	(54.34)
Group 1 (Most Efficient)	644.1***	7.939	46.97	462.3***	-4.042	179.9***
	(130.2)	(49.26)	(50.39)	(87.34)	(67.80)	(67.86)
Group 2	57.21	5.625	44.66	414.6***	-128.1***	55.87*
	(109.5)	(29.18)	(31.04)	(88.74)	(28.93)	(28.97)
Group 3		-0.418	-6.444***		1.219	0.434
		(1.508)	(2.138)		(1.377)	(2.174)
Group 4	-85.44	43.47**	18.30	-79.03	1.271	-8.558
	(81.51)	(18.14)	(18.18)	(83.40)	(10.47)	(22.06)
Group 5 (Least Efficient)	-87.76	2.877	0.295	-203.1***	4.621**	1.850
	(71.14)	(2.450)	(2.987)	(56.42)	(2.178)	(3.591)
Group 1 * Trend	4.265	4.682	10.71	-6.986	-8.206	-7.421
	(7.629)	(7.761)	(7.909)	(4.870)	(5.052)	(5.328)
Group 2 * Trend	2.306	2.724	8.750	-15.92***	-17.14***	-16.35***
	(6.241)	(6.407)	(6.585)	(4.266)	(4.476)	(4.784)
Group 3 * Trend	-4.804	-4.386	1.640	4.841	3.622	4.407
	(4.613)	(4.844)	(5.076)	(4.376)	(4.581)	(4.883)
Group 4 * Trend	-3.300	-2.882	3.144	-4.915	-6.134	-5.349
	(2.024)	(2.521)	(2.942)	(3.796)	(4.032)	(4.371)
Group 5 * Trend	-0.665	-0.247	5.779**	1.584	0.364	1.149
	(1.830)	(2.368)	(2.812)	(1.363)	(1.936)	(2.565)
Group 1 * Standard	-38.25	-81.72	-56.55	-20.19	-21.46	-11.63
	(84.51)	(86.26)	(86.29)	(35.32)	(36.78)	(41.62)
Group 2 * Standard	48.34	4.871	30.04	-10.40	-11.67	-1.845
	(66.78)	(69.07)	(69.09)	(41.98)	(43.20)	(47.39)
Group 3 * Standard	94.16	50.69	75.86	-35.77	-37.04	-27.21
	(73.63)	(75.68)	(75.70)	(22.48)	(24.76)	(31.48)
Group 4 * Standard	-36.65*	-80.12***	-54.95*	28.82	27.55	37.38
	(21.93)	(28.43)	(28.46)	(25.17)	(27.22)	(33.45)
Group 5 * Standard	-19.78	-63.25*	-38.08	-43.15**	-44.43**	-34.60
	(31.71)	(36.47)	(36.49)	(19.28)	(21.91)	(29.29)
Group 1 * Trend * Standard	-13.04	-15.92*	-13.33	1.191	-3.430	-0.659
	(9.028)	(9.336)	(9.493)	(6.226)	(6.586)	(7.182)
Group 2 * Trend * Standard	-5.029	-7.906	-5.324	5.180	0.559	3.330
	(7.488)	(7.863)	(8.048)	(6.262)	(6.619)	(7.213)
Group 3 * Trend * Standard	-0.387	-3.264	-0.682	-2.055	-6.675	-3.905
	(6.503)	(6.936)	(7.145)	(6.489)	(6.834)	(7.411)
Group 4 * Trend * Standard	3.188	0.311	2.893	0.446	-4.174	-1.404
	(2.959)	(3.837)	(4.201)	(3.736)	(4.319)	(5.179)
Group 5 * Trend * Standard	-5.317*	-8.195**	-5.612	-2.291	-6.912**	-4.141
	(3.057)	(3.913)	(4.270)	(2.579)	(3.372)	(4.419)
Constant	560.9***	467.5***	428.4***	616.4***	541.4***	357.4***
	(66.39)	(14.17)	(17.68)	(51.48)	(17.50)	(17.54)
Model Fixed Effects	N	N	N	N	N	N
Observations	3,073	6,719	5,858	4,493	10,355	6,829
R-squared	0.501	0.410	0.509	0.364	0.253	0.444

Standard errors in parentheses clustered by model number
*** p<0.01, ** p<0.05, * p<0.1

Note: Results for regressions estimating the concurrent effect of the new standard (either 2004 or 2007) on the average price of clothes washers differentiated across efficiency categories. Columns (1) and (4) only include clothes washer models, while Columns (2) and (5) look at the effect relative to dryers, and Columns (3) and (6) look at the effect relative to room ACs. No controls or fixed effects are included other than the efficiency categorizations.

I first discuss the results from the efficiency-level price regressions with no fixed effects, these regressions are presented in Table 2.7. There were no statistically significant average price changes within any of the three highest efficiency segments (Groups 1, 2 or 3) at either standard change. On the other hand, average prices dropped for either Group 4 or Group 5 (the least efficient market segments), or both, in all but one specification. In particular, Group 4 average prices dropped $36.65 ($80.12 relative to dryer, and $54.95 relative to room ACs) at the 2004 standard change, but did not change significantly at the 2007 standard change. Additionally, Group 5 average prices dropped significantly $43.15 ($44.43 relative to dryer, and not significantly relative to room ACs) at the 2007 standard change, and also experienced a marginally significant $63.25 price drop relative to dryers at the 2004 standard change.

There is slight evidence of a downward trend-break in two market segments. In particular, there was a marginally significant downward trend-break in Group 1 average prices of $15.92 per month relative to dryers following the 2004 standard. Also for Group 5 there was a downward trend-break of $5.32 per month in the first differences regression ($8.20 relative to dryers) at the 2004 standard change, and $6.91 relative to dryers at the 2007 standard change. However, realize that in general mid-high efficiency categories, particularly Group 2, tended to have average prices that trended down more quickly overall relative to all other categories and relative to both counterfactuals at a rate of between $15 to $17 per month over the 2006-2007 two year period.

Note, once again, that if the standard resulted only in cheaper low-efficiency models being dropped from the market – with no other price or menu adjustments – the lowest efficiency categories would be expected to experience a price increase on average. These results begin to paint a very different picture, indicating that the downward pressure on prices at the time of the standard changes tended to be driven by these least efficient categories. This story is only strengthened when looking at the results for the within-model price changes presented in Table 2.8 discussed next.

I now turn to the results of the efficiency-group specific regressions including fixed effects, presented in Table 2.8. In addition to fixed effects, I also control for the FTC kWh/year measure of efficiency in the Column (1) and (4) regressions. This is because, as mentioned above, the kWh/year measure does change within-model for a handful of models. I cannot include this variable in the estimation when counterfactuals are included in Columns (2), (3), (5) or (6) because this variable is not defined for dryers or room ACs.

Table 2.8: Within-Model Price Effects at New Standard Effective Dates: Efficiency-Level Specific Results

	2004 Standard Change			2007 Standard Change		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var: Price	No Controls	Dryers as Controls	Room AC as Controls	No Controls	Dryers as Controls	Room AC as Controls
Trend		-3.600***	-7.083***		-5.159***	-2.328***
		(0.548)	(0.905)		(0.648)	(0.796)
Standard		-1.683	36.10***		-2.954	14.50*
		(4.285)	(7.228)		(4.204)	(7.638)
Trend * Standard		0.413	0.762		-2.438**	-0.744
		(0.973)	(1.171)		(0.984)	(1.307)
Group 1 (Most Eff) * Trend	-6.720*	-3.105	0.378	-9.077***	-3.957*	-6.787***
	(3.824)	(3.832)	(3.949)	(2.144)	(2.248)	(2.315)
Group 2 * Trend	-4.161*	-0.170	3.313	-11.40***	-6.138**	-8.968***
	(2.229)	(2.189)	(2.330)	(2.250)	(2.382)	(2.447)
Group 3 * Trend	-3.042***	0.699	4.182***	-5.331***	0.281	-2.550
	(0.835)	(0.953)	(1.201)	(1.423)	(1.618)	(1.695)
Group 4 * Trend	-4.912***	-1.858*	1.625	-2.378***	2.936***	0.106
	(0.995)	(1.068)	(1.297)	(0.825)	(1.025)	(1.130)
Group 5 (Least Eff)* Trend	-1.718	1.693	5.176***	-2.077**	3.082**	0.252
	(1.141)	(1.245)	(1.450)	(1.033)	(1.218)	(1.311)
Group 1 * Standard	-30.83	-28.26	-66.04**	2.391	4.781	-12.67
	(28.63)	(28.89)	(29.84)	(16.17)	(16.68)	(17.99)
Group 2 * Standard	-27.87	-20.48	-58.27	-7.496	-9.252	-26.71
	(36.17)	(36.42)	(37.36)	(19.34)	(19.24)	(20.44)
Group 3 * Standard	-41.34***	-14.38	-52.17***	-23.93*	-26.78**	-44.23***
	(15.04)	(11.87)	(13.35)	(13.12)	(12.20)	(13.85)
Group 4 * Standard	-95.64***	-90.51***	-128.3***	-8.402	-6.722	-24.18**
	(27.47)	(27.50)	(28.47)	(8.242)	(9.000)	(11.09)
Group 5 * Standard	-60.06***	-34.64**	-72.42***	-25.63**	-22.66*	-40.12***
	(17.66)	(15.32)	(16.57)	(12.48)	(13.15)	(14.72)
Group 1 * Trend * Standard	-6.157	-6.582	-6.931	-5.921**	-3.450	-5.144*
	(4.446)	(4.516)	(4.620)	(2.807)	(2.977)	(3.123)
Group 2 * Trend * Standard	-3.808	-4.566	-4.914	-9.932**	-7.714*	-9.408**
	(2.972)	(3.051)	(3.156)	(3.861)	(4.014)	(4.140)
Group 3 * Trend * Standard	-1.821	-2.378	-2.727	-4.639*	-2.423	-4.117
	(1.235)	(1.567)	(1.709)	(2.607)	(2.910)	(3.058)
Group 4 * Trend * Standard	0.741	0.872	0.524	-4.382***	-2.126	-3.820*
	(1.142)	(1.480)	(1.627)	(1.631)	(1.878)	(2.078)
Group 5 * Trend * Standard	-1.981	-1.962	-2.310	-4.143*	-1.706	-3.400
	(1.465)	(1.750)	(1.883)	(2.190)	(2.398)	(2.566)
FTC kWh/year	-0.121**			1.119*		
	(0.0526)			(0.571)		
Constant	835.8***	636.0***	602.5***	427.9**	713.7***	659.3***
	(36.10)	(6.454)	(7.541)	(191.6)	(5.101)	(5.975)
Model Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	3,073	6,719	5,858	4,493	10,355	6,829
R-squared	0.293	0.239	0.258	0.422	0.356	0.375
Number of Models	333	651	705	402	930	722

Standard errors in parentheses clustered by model number
*** p<0.01, ** p<0.05, * p<0.1

Note: Results for regressions estimating the concurrent effect of the new standard (either 2004 or 2007) on the within-model price of clothes washers differentiated across efficiency categories. Columns (1) and (4) only include clothes washer models, while Columns (2) and (5) look at the effect relative to dryers, and Columns (3) and (6) look at the effect relative to room ACs. Model-specific fixed effects are included in all specifications. The FTC kWh/year variable is included only in the regressions presented in columns (1) and (4) because this variable in not defined for dryers or room ACs.

Once again, the results indicate that the drop in prices, here measured as the drop in within-model prices, appears to be driven by the lowest efficiency groups. There are no statistically significant discontinuous price drops for the two highest efficiency groups (1 or 2) in any specification save one, which indicates that Group 1 within-model prices dropped \$66.04 on average relative to the similar price drop of room ACs at the 2004 standard change. On the other hand, Groups 3, 4 and 5 experienced statistically significant price dropped in most cases. In particular, Group 3 experienced a price drop of \$41.34 at the 2004 standard change (no significant change relative to dryer, but a significant \$52.17 drop relative to room ACs). Additionally, Group 3 experienced a statistically significant within-model price drop at the 2007 standard change in all three specifications: \$23.93 in the first-differences regression, \$26.78 relative to dryers, and \$44.23 relative to room ACs. Group 4 saw the largest and across-the-board significant within-model price drops at the 2004 standard change: \$95.64 in the first-differences regression, \$90.51 relative to dryers and \$128.3 relative to room ACs. Group 4 also saw a significant \$24.18 within-model price drop at the 2007 standard change relative to room ACs. Finally, Group 5 experienced statistically significant within-model price drops in all cases. At the 2004 standard change this price drop ranged from \$34.64 relative to dryers to \$60.06 in first differences and \$72.42 relative to room ACs. Then, at the 2007 standard change, Group 5 experienced smaller within-model price drops ranging from a marginally significant \$22.66 relative to dryers and \$25.63 in first-differences, to \$40.12 relative to room ACs.

These coefficients can be a lot to keep track of, so I have provided Figure 2.5, which summarizes the results of these discontinuous changes in price coincident with the standard changes. This figure makes clear that the discontinuous drop in prices was driven by the lowest efficiency groups at both standard changes.

In terms of trend results it is clear again that the highest efficiency groups tended to have within-model prices that trended downward more quickly on average, both overall in the two years surrounding each standard, and in terms of a trend-break at the standard changes. In 2003/2004 the within-model prices of Groups 1, 3 and 4 were trending downward most quickly overall, however, in 2006/2007 this downward within-model price trend was concentrated in the highest efficiency groups (1 and 2). There were no statistically significant breaks in trend following the 2004 standard change in any groups. However, following the 2007 standard change, the within-model price trends of the two most efficient groups (1 and 2), already trending downward at the highest rate, experienced additional significant downward breaks in trend.

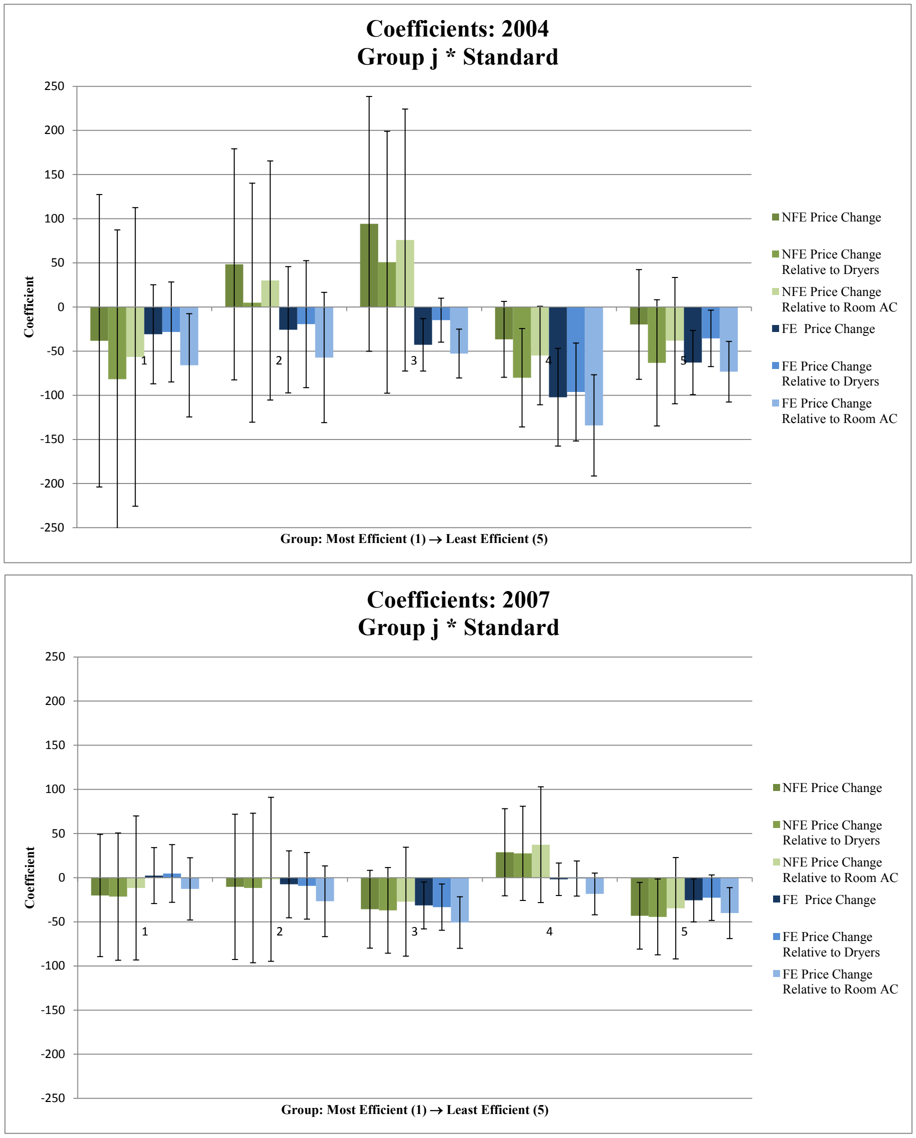
The trend effects – limited to the within-model effects – across the groups are presented in Figure 2.6, which presents the combined within-model trend terms (i.e. the sum of the coefficient on $Group_{ji} * Trend_t$ and on $Standard_t * Group_{ji} * Trend_t$). Figure 2.6 makes clear that the within-model prices of the highest efficiency groups were trending down most quickly at the time of both standard changes. These results are consistent with a pattern of newer/more efficient models being priced at a higher level initially, and dropping in price more quickly relative to older/less efficient models. This could be due to strategic intertemporal price discrimination strategies by firms, "learning-by-doing" reductions in production costs, or both.

I now relate these results explicitly to the predictions of the model presented in Section 2.2. Recall price discrimination predicted that the models decertified from Energy Star should see an immediate price drop, and models that are close substitutes to those for which the minimum standard is binding should see an immediate price decrease (i.e. the lower efficiency categories). This is in contrast to the perfectly competitive model, in which the lower efficiency segments of the market should see an increase in price, or at least no decrease.

Looking first at the top panel of Figure 2.5 summarizing the price level effects for the 2004 standard change, you can see that Group 4 and Group 5 – the two least efficient groups – saw a significant and robust price drop, which is inconsistent with a perfectly competitive model, but consistent with the model which allows for price discrimination. Additionally, this price drop is seen for Group 3 when looking at the within-model price change, though not for the average price specifications. The predictions of the model allow for an ambiguous effect around the middle and high-end of the market, which is what we see here. If any models were decertified from Energy Star in 2004, we should see a price drop at the mid-high end of the market, which we do see to a certain extent in the within-model price change for Group 3, though this does not seem to be an obvious effect. In sum, the level drop in prices appears to be driven by the low end of the market in 2004, providing support for the price discrimination hypothesis.

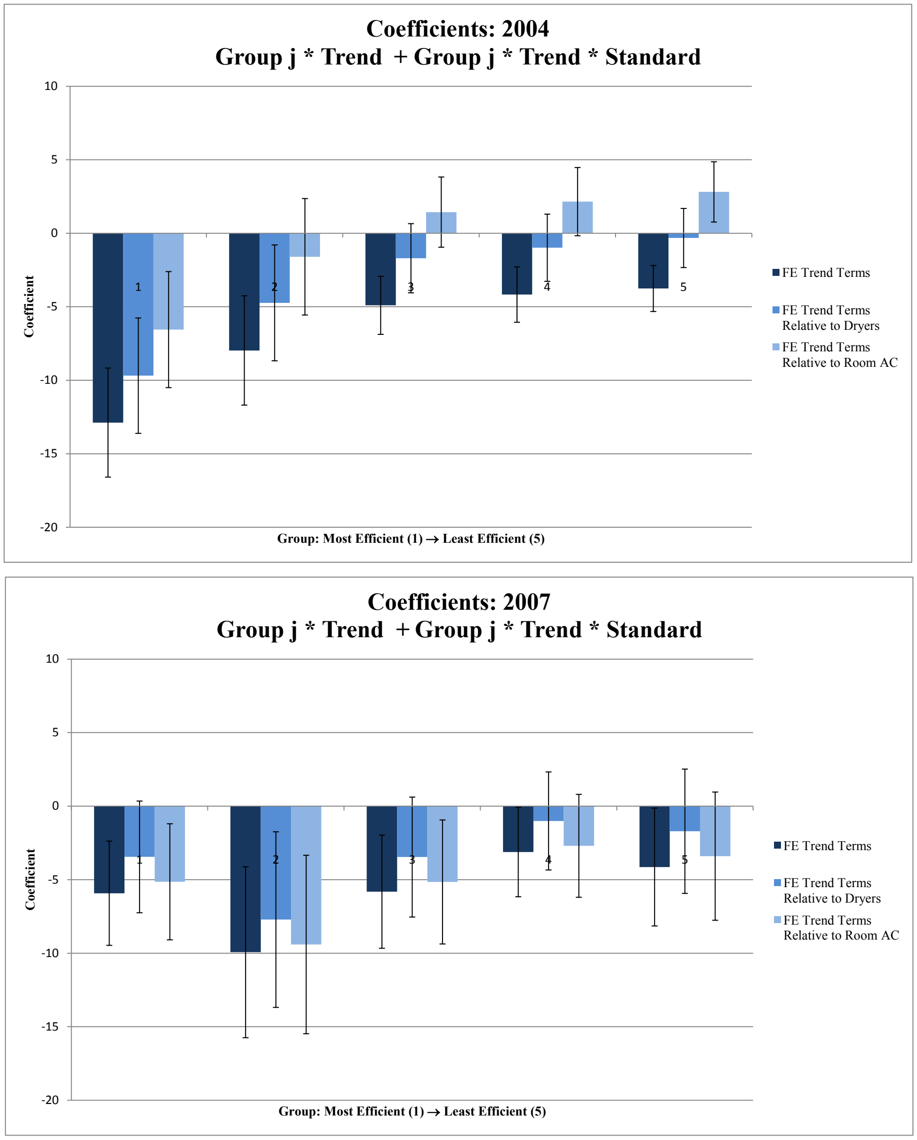
Turning now to the price level effects from 2007 presented in the bottom panel of Figure 2.5, we see the same pattern as for 2004, but with smaller magnitudes. In particular, for Groups 5 and 3 we see significant price drops, particular within-model, with no consistent effects for the other groups. Once again, this price drop for the lowest efficiency group is inconsistent with the perfectly competitive model, but consistent with the predictions of the price-discrimination model.

Figure 2.5: Coefficients from Efficiency-Level Regressions: Level Effect



Note: Coefficients from regressions presented in Tables 2.7 and 2.8. The top panel shows the level-effect of the standard on prices across the five efficiency categories for the 2004 standard, and the bottom panel shows the same results for the 2007 standard. The 95% confidence interval is shown for each coefficient.

Figure 2.6: Coefficients from Efficiency-Level Regressions: Within-Model Trends

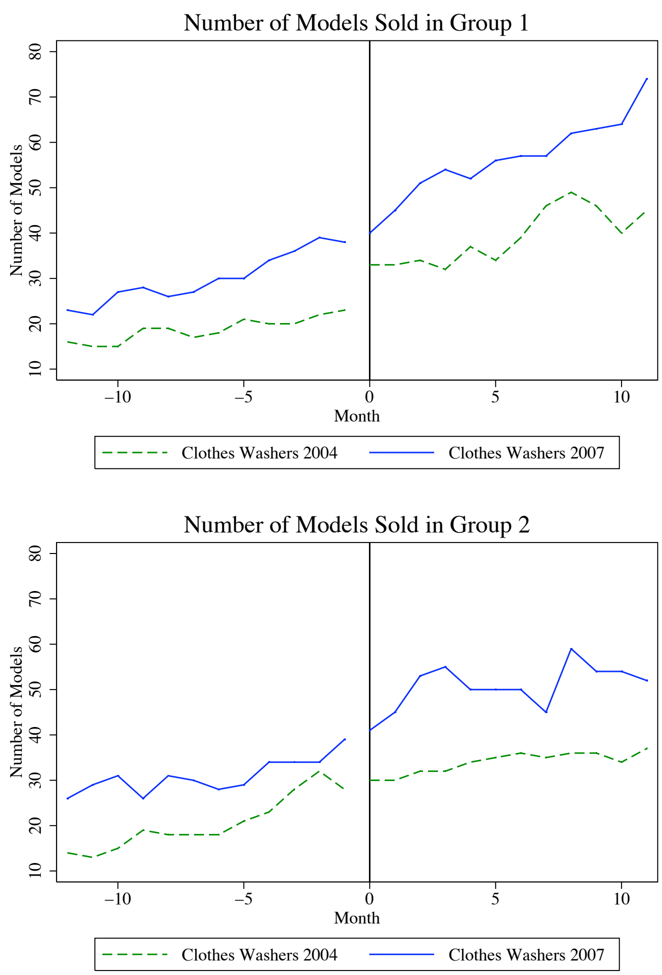


Note: Sum of trend coefficients from regressions presented in Table 2.8. The top panel shows the within-model price trends across the five efficiency categories at the 2004 standard, and the bottom panel shows the same results for the 2007 standard. The bars are the sum of the coefficients on $Group_{ji} * Trend_t$ and $Standard_t * Group_{ji} * Trend_t$. The 95% confidence interval for this combined term is shown.

2.4.3 Testing Model Prediction: Menu Adjustment

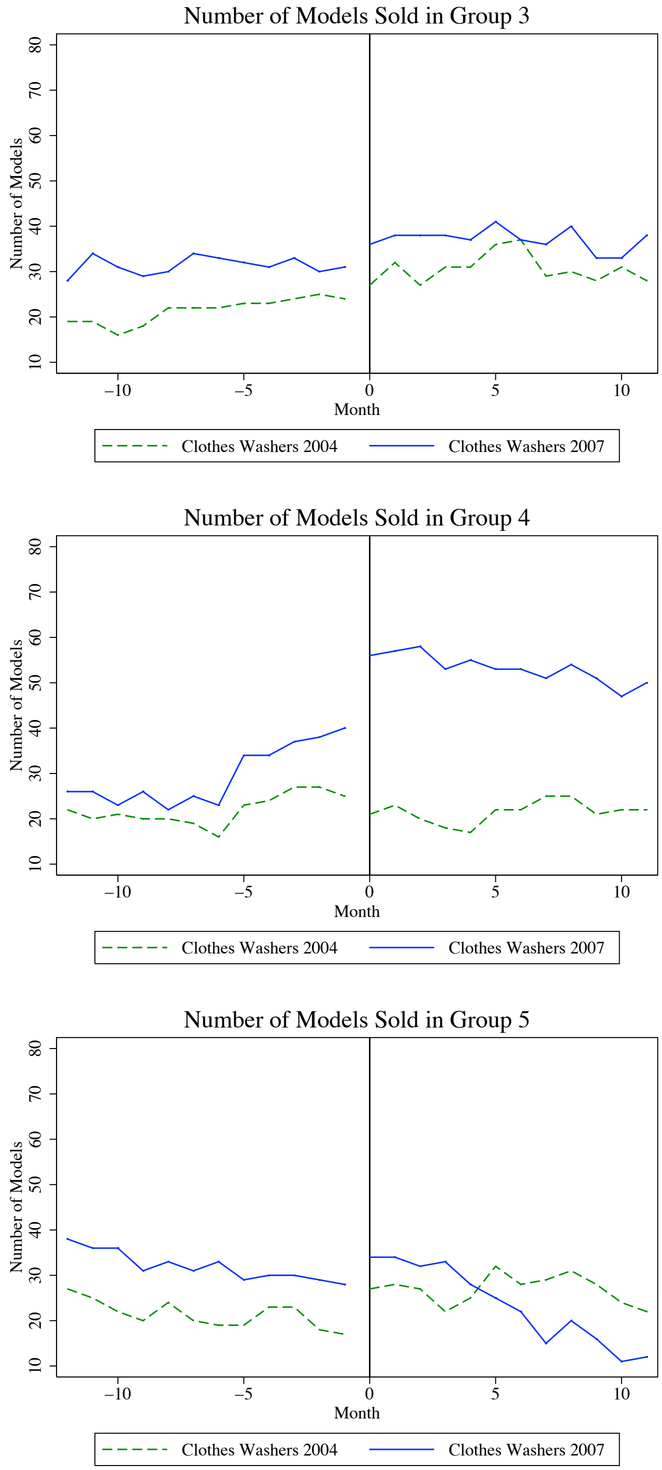
The second prediction of the imperfect competition model is that firms will spread efficiency upwards to alleviate price competition across the market after the new standard restricts the efficiency distribution. Figures 2.7 and 2.8 demonstrates evidence of this pattern, showing the total number of individual models offered in each efficiency group around the standard change dates. In particular, the lowest efficiency group (5) sees a drop-off in the number of models available in the market, particularly following the 2007 standard. This is what we'd expect given the standard will cause some models to exit the market as they no longer meet the minimum requirement of the standard. More interestingly, we see a distinct increase in the number of models offered in the highest efficiency group (1). This is consistent with firms spreading efficiency upward to alleviate the increased price competition across their products as a result of the standard.

Figure 2.7: Proliferation of New Models in Market by Efficiency Category (Groups 1 and 2)



Note: Total number of individual model numbers within each efficiency category that were sold in each time period for the year just prior to, and the year just following, each new standard.

Figure 2.8: Proliferation of New Models in Market by Efficiency Category (Groups 3, 4 & 5)



Note: Total number of individual model numbers within each efficiency category that were sold in each time period for the year just prior to, and the year just following, each new standard.

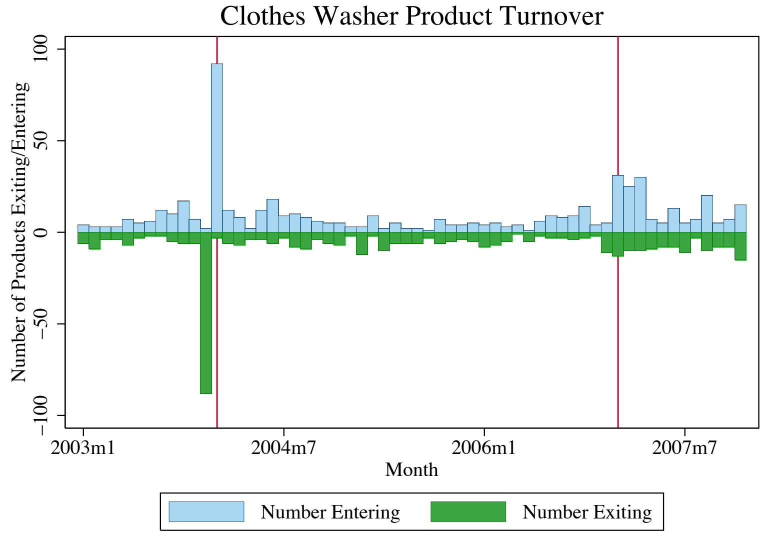
2.4.4 Firm Response Strategies in 2004 versus 2007

The results from Section 2.4.2, while indicating prices tend to be depressed following the standard changes – and drop discontinuously to the largest extent for the lowest efficiency groups – do indicate differences between the standard change in 2004 versus 2007. One would expect that firms might respond differently to these two standard changes for several reasons. First, both standards were adopted in 2001 as part of the same standard rule-making. Therefore, it stands to reason firms had more time to adapt to the 2007 standard than to the 2004 standard. Also, the previous standard affecting the clothes washer market prior to 2004 was effective in 1994, meaning that at the time the standard changed in 2004, 10 years had elapsed since the last tightening of the minimum efficiency standard. One might expect, therefore, that adaptation strategies might be relatively prevalent or inexpensive in 2004, whereas three years later in 2007, the inexpensive options had already been exhausted and so other strategies were likely implemented. This section explores the differences in the apparent strategies used to adapt to these two standards, and relates these differences to the differences in price effects across the efficiency groups presented in Section 2.4.2.

Figure 2.9 depicts the frequency of individual model numbers entering and exiting the market at each month in the study period. A model number is said to exit the market in month t if the last observation of that model occurs in month t. Similarly a model is said to enter the market in month t if the first time that model appears in the data is in month t. It is immediately apparent looking at this figure that close to 100 models exited the market in December 2003 (well over half the models in the market), and close to 100 entered in January 2004. However, the vast majority of models exiting the market in December 2003 have the same model number, except one or two characters, as models entering in December 2004, while the energy use level of these matched-pairs drops. For example, Whirlpool model GHW9250M exited the market in December 2003, having an FTC rating of 294 kWh/year, while Whirlpool model GHW9250ML entered the market in January 2004, having an FTC rating of 285 kWh/year. This pattern is not observed to nearly the same extent at the 2007 standard change. This indicates firms likely made small internal adjustments to existing models in order to come into compliance with the new standard in 2004. These inexpensive changes were likely exhausted by the time the 2007 standard came along, however, requiring that firms respond by eliminating more low-end models, rather than bringing them into compliance.[29]

[29] Appendix B.5 provides a figure that shows the same frequency of models entering and exiting, but does so specifically within each efficiency group. It is clear that the models being adapted and swapped-out in 2004 were not only models at the low end of the efficiency spectrum. This indicates that models were likely being adapted not only to meet the new minimum standard, but that mid-range products that had been Energy Star before the standard were adapted to meet the new Energy Star standard as well. Therefore, it is possible that few models were disqualified from Energy Star in 2004.

Figure 2.9: Model Entry and Exit From Market by Date



Note: Frequency of models entering and exiting the data in each month in the sample for years 2003 through 2007. The occurrences of the combined change in minimum and Energy Star standards are indicated by the vertical lines. The upward-facing histogram indicates frequency of new models entering the data, while the downward-facing histogram indicates frequency of models exiting the data.

How do these results relate to the results presented in Section 2.4.2 and 2.4.3? First, prior to 2004 it is reasonable to assume that firms had been engaging in more or less their optimal pricing strategy given market conditions. If they were price discriminating, they were under-providing efficiency to the customers with the lowest willingness to pay, and charging positive margins on all products in the market. Additionally, these positive margins increased in magnitude moving up the efficiency spectrum. Then the 2004 standard was imposed, which forced them to increase the efficiency level of the lowest type of products, eliminating that essential lever that had allowed them to charge high margins on higher efficiency products. This forced them to drop the prices of products that were close substitutes to those eliminated by the standard (Groups 3, 4 and 5), which we see in the regression results and is predicted by the price discrimination model. Then, at the time the 2007 standard came into effect, margins were already depressed from the relatively recent 2004 standard, and inexpensive adaptation strategies had already been exhausted. For this reason the price drop in the lowest efficiency categories is of a lower magnitude relative to the drops seen in 2004. In both cases the range of efficiency is restricted by the standard and firms respond by spreading efficiency upward to alleviate competition across the spectrum of their products. However, we see products dropping out of the lowest efficiency group and proliferating in the highest efficiency group more so in 2007 than 2004, which corroborates the theory that firms were modifying existing models to meet the new standards more in 2004, while dropping and introducing completely new models more in 2007.

2.5 Conclusion

Beginning in 1987, the United States federal government has set minimum energy efficiency standards for more than 55 products. Some have questioned the justifiability of minimum efficiency standards for appliances as implemented by the DOE. For example, Gayer and Viscusi (2012) make the following argument:

> The impetus for the new wave of energy efficiency regulations has little to do with externalities. Instead, the regulations are based on an assumption that government choices better reflect the preferences of consumers and firms than the choices consumers and firms would make themselves. In the absence of these claimed private benefits of the regulation, the costs to society dwarf the estimated benefit.

They argue that if the purchase of a more efficient appliance resulted in a net benefit to consumers, they would already have made the purchase, ergo the imposition of a standard eliminating certain models from the market must result in a net welfare loss. Much of the literature discussing the "Energy Efficiency Gap,"[30] and the accompanying justification for minimum efficiency standards, suggests that consumers have some form of bounded rationality (they do not pay attention to, or hyperbolically discount, future savings in operating costs from a more efficient product). While evidence exists that consumers do exhibit these types of preferences/behaviors,[31] Gayer and Viscusi (2012) among others believe the idea that the government "knows better" than consumers is an unjustified paternalistic attitude. However, the argument Gayer and Viscusi (2012) make against minimum efficiency standards assumes appliance markets are perfectly competitive. In a perfectly competitive market, setting aside any question of environmental externalities, everyone has full information, no single firm can strategically influence the market price, and the equilibrium – absent any policy intervention – maximizes social welfare. If, however, the market is not perfectly competitive, but rather consists of firms with the capability to price discriminate, then a minimum efficiency standard directly addresses this market failure.

I have presented a model of second-degree price discrimination in a quality-differentiated market for household durables based on the classic work by Mussa and Rosen (1978), as well as Ronnen (1991), De Meza and Ungern-Sternberg (1982), Katz (1984), and Crampes and Hollander (1995). I have adapted this model to the Unites States clothes washer market, and extended the model to allow for a change in the Energy Star standard concurrent to the change in minimum efficiency standard. This market has a high degree of market concentration with one firm, Whirlpool, holding close to 60% of the market share according to the data used in this analysis. Assuming consumers have heterogeneous preferences for energy efficiency (possibly due to heterogeneous discount rates or environmental attitudes), firms with market power have an incentive to under-provide efficiency at the low end of the market, allowing them to charge positive and increasing margins on all other efficiency levels moving up the efficiency distribution of products. Imposing a minimum efficiency

[30] The term "Energy Efficiency Gap" is used to describe the observation that consumers apparently are not purchasing products that have a positive NPV.

[31] An excellent summary of the empirical evidence of several types of non-standard preferences can be found in DellaVigna (2009).

standard in this setting forces price-discriminating firms to drop prices, particularly of the lowest efficiency categories just above those eliminated by the new standard. In a perfectly competitive market on the other hand, one would expect prices of the lowest efficiency categories to increase.

I find evidence of an average drop in the prices of clothes washers at the times of the standard changes. Both in 2004 and 2007, prices dropped predominantly within-model, although the overall price distribution did not appear to significantly change at either standard change date.

In addition, I show that at both standard changes, the prices of the three lowest efficiency groups dropped the most. This result is inconsistent with a perfectly competitive market, while explicitly predicted by an imperfectly competitive market in which firms have been engaged in second-degree price discrimination.

I show evidence that along with a level drop in prices at the time the new standards went into effect, price trends broke downward, particularly following the 2007 standard change. The within-model downward trend in prices was particularly pronounced in the higher efficiency categories. This is consistent with the idea that firms experience some "learning-by-doing" in the production process when new technologies or innovations are introduced in the market. It is also consistent with firms engaged in intertemporal price discrimination.

I show, as well, evidence of an increased proliferation of new models in the highest efficiency range of products following both standard changes. This is consistent with firms attempting to spread the efficiency distribution upwards following the restriction imposed by the new standard. Ronnen (1991) and Crampes and Hollander (1995) predict this behavior, which is the result of firms attempting to alleviate price competition across the efficiency spectrum.

Additionally, I provide evidence that firms adapted many models to meet the 2004 standard, rather than eliminating them from the market. I do not see this pattern to the same extent in 2007.

Prices dropped by a smaller magnitude at the time of the 2007 standard change, relative to the 2004 standard change. This is consistent with margins having already been reduced for these groups at the standard change in 2004, leaving less room to drop prices when the standard changed in 2007. This last point is important from a policy perspective, as there is some debate about how frequently standards should be imposed. Indeed, results from Chen, Dale, and Roberts (2013) and those presented here, indicating that standards tend to have a negative effect on prices, could lead some to push for more frequent standard changes. However, looking at the difference in magnitudes of the price drops in 2004 relative to 2007 should introduce a note of caution into the debate. Prices can only decrease so far before margins have no further room to drop. More frequent standards might lead to price increases, even if firms still hold power in the market, but do not have time to adapt technology, product menu, and prices following one standard before another is imposed.

This analysis provides direct evidence that the market for clothes washers is not perfectly competitive and that firms in this market have historically engaged in second-degree price discrimination. Therefore, quite aside from arguments about the role of government in rectifying the apparent "Energy Efficiency Gap," which have been seen as paternalistic at best by some, this paper demonstrates that minimum efficiency standards are justified, and indeed desirable, from a classic economic perspective, as standards directly address the imperfect competition market failure in this quality-differentiated market.

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Appendix A: Appendices for Chapter 1

Appendix A.1: Treatment Prices for CPP & TOU Households

Table A.1: SPP Treatment Rates

CPP High Ratio

Utility	Reference Price (8/1/2003)	Off-Peak Credit Summer	Off-Peak Credit Winter	Regular Peak Surcharge Summer	Regular Peak Surcharge Winter	Critical Peak Surcharge Summer	Critical Peak Surcharge Winter
SCE	0.1503	-0.0550	-0.02604	0.1123	0.20650	0.6050	0.42893
PG&E	0.1791	-0.0495	-0.02492	0.1011	0.18208	0.5445	0.38008
SDG&E	0.1702	-0.0550	-0.02657	0.1123	0.20346	0.6050	0.42346
SCE (CARE)	0.0976	-0.0475	-0.02357	0.0864	0.16035	0.4805	0.33628
PG&E (CARE)	0.0931	-0.0397	-0.02001	0.0808	0.14559	0.4355	0.30399
SDG&E (CARE)	0.1263	-0.0382	-0.01543	0.0956	0.16859	0.4898	0.34459

CPP Low Ratio

Utility	Reference Price (8/1/2003)	Off-Peak Credit Summer	Off-Peak Credit Winter	Regular Peak Surcharge Summer	Regular Peak Surcharge Winter	Critical Peak Surcharge Summer	Critical Peak Surcharge Winter
SCE	0.1503	-0.0200	-0.01491	0.0833	-0.01012	0.3969	0.57439
PG&E	0.1791	-0.0144	-0.01502	0.0846	-0.01052	0.3726	0.53848
SDG&E	0.1702	-0.0160	-0.01723	0.0940	-0.01223	0.4140	0.59777
SCE (CARE)	0.0976	-0.0195	-0.01466	0.0632	-0.01060	0.3140	0.48527
PG&E (CARE)	0.0931	-0.0116	-0.01209	0.0676	-0.00849	0.2980	0.43071
SDG&E (CARE)	0.1263	-0.0070	-0.00796	0.0810	-0.00396	0.3370	0.48404

TOU High Ratio

Utility	Reference Price (8/1/2003)	Off-Peak Credit Summer	Off-Peak Credit Winter	Regular Peak Surcharge Summer	Regular Peak Surcharge Winter	Critical Peak Surcharge Summer	Critical Peak Surcharge Winter
SCE	0.1503	-0.0350	-0.00659	0.1220	0.05341	-	-
PG&E	0.1791	-0.0315	-0.00446	0.1098	0.05405	-	-
SCE (CARE)	0.0976	-0.0315	-0.00732	0.0941	0.04423	-	-
PG&E (CARE)	0.0931	-0.0253	-0.00364	0.0878	0.04316	-	-

TOU Low Ratio

Utility	Reference Price (8/1/2003)	Off-Peak Credit Summer	Off-Peak Credit Winter	Regular Peak Surcharge Summer	Regular Peak Surcharge Winter	Critical Peak Surcharge Summer	Critical Peak Surcharge Winter
SCE	0.1503	-0.0050	-0.03250	0.0800	0.07561	-	-
PG&E	0.1791	-0.0045	-0.02642	0.0720	0.07258	-	-
SCE (CARE)	0.0976	-0.0075	-0.02885	0.0605	0.05837	-	-
PG&E (CARE)	0.0931	-0.0037	-0.02121	0.0575	0.05799	-	-

Appendix A.2: Data Cleaning and Robustness Checks

- I dropped 17 control households because they only appeared in the data for 32 days or less (resulted in dropping less than 0.3% of control observations).

- The usage data, recorded at 15 minute increments, had some scattered missing observations. If 15 minute increment observations were missing for days in which most of the other 15 minute increments were not missing, I filled in the missing 15 minute increments with average values for the appropriate periods (peak or off-peak) from the rest of that day, and then aggregated up to the daily level. Less than 0.5% of the daily observations were affected in this way.

- For some of the households, bill period (including bill period begin and end dates) were missing for a subset of the observations. I filled in the bill period end and begin dates based on the average length of the bill period for that household. Less than 0.1% of observations were affected by this. Four households (3 TOU households and 1 control household) were dropped because they had more than 10% of their own observations filled-in in this way. For the remaining households on average less than 0.06% of observations per household (a total of 8% of observations overall) had bill period end/begin dates that were filled-in in this way.

- For some reason, all the weather data for PG&E customers was missing for August 2003. I filled in the weather variables for these customers with their average values of July and October for that year. As a robustness check I run the daily peak consumption regressions dropping August 2003 data for PG&E and find no significant difference in the results.

- Other than the August 2003 PG&E missing weather data, weather data were missing for a handful of other scattered observations. If weather data was missing for a few days for a weather station, I filled in the missing weather variable with the average values for the surrounding few days. In total 0.05% of observations had filled in weather data in this way.

- A total of 230 households left the treatment early (including households from all groups), 109 of these households (41 CPPH, 43 CPPL, 25 TOU households) appear to have left most likely not because they moved away, but rather because they dropped out. These households were kept in the analysis for the observations for which they were in treatment.

Table A.2: Peak kWh Robustness Checks: CPP vs Control

Dependent Variable: Peak kWh						
	(1)	(2)	(3)	(4)	(5)	(6)
	Drop Dropouts	Drop Aug.2003 PG&E	Drop Dropouts	Drop Aug.2003 PG&E	Drop Dropouts	Drop Aug.2003 PG&E
T=1: CPP T=0: Control	D = Number of critical peak days so far		D = Number of critical peak days in week 1		D = Peak temperature in week 1	
C ($b_{1,p}$)	1.027***	1.043***	0.601***	0.653***	0.575***	0.604***
	(0.141)	(0.148)	(0.116)	(0.125)	(0.0985)	(0.107)
D ($b_{2,p}$)	0.0515*	0.0495*	0.0603	0.0836	0.0998***	0.0983***
	(0.0286)	(0.0294)	(0.0661)	(0.0667)	(0.0128)	(0.0134)
T * C ($b_{4,p}$)	-1.445***	-1.444***	-1.315***	-1.307***	-1.134***	-1.116***
	(0.193)	(0.197)	(0.175)	(0.183)	(0.143)	(0.150)
T * D ($b_{5,p}$)	-0.0968***	-0.0992***	-0.240***	-0.232***	-0.0676***	-0.0639***
	(0.0346)	(0.0349)	(0.0731)	(0.0741)	(0.0170)	(0.0170)
Summer Pricing	-0.0774	-0.0869	0.139*	0.117	0.119	0.121
	(0.0742)	(0.0751)	(0.0841)	(0.0837)	(0.0855)	(0.0854)
Peak Degree Hours	0.172***	0.173***	0.191***	0.189***	0.173***	0.173***
	(0.00768)	(0.00752)	(0.00823)	(0.00810)	(0.00717)	(0.00707)
Constant	4.238***	4.230***	3.949***	3.974***	3.401***	3.383***
	(0.119)	(0.121)	(0.142)	(0.144)	(0.177)	(0.182)
Day-of-week effects	Y	Y	Y	Y	Y	Y
Month-of-year effects	Y	Y	Y	Y	Y	Y
Household fixed effects	Y	Y	Y	Y	Y	Y
Daily Observations	184,969	188,078	144,014	143,653	144,014	143,653
R-squared (within)	0.165	0.165	0.180	0.178	0.190	0.187
Total Number of Households	1,003	1,075	999	1,066	999	1,066

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, *p<0.1

Note: Results of fixed-effect regressions exploring the correlation of daily peak kWh usage during a subsample of days in the experiment and a set of explanatory variables. The CPPL and CPPH treatment groups are pooled and the Control group is used as the counterfactual. These regressions are reproductions of those presented in Table 1.3. Columns (1), (3) and (5) present the results of the regressions after the households that dropped out of the experiment partway through have been dropped. Columns (2), (4) and (6) present the results of the regressions after days in August 2003 for PG&E households have been dropped.

Table A.3: Peak kWh Robustness Checks: CPP vs TOU

Dependent Variable: Peak kWh	(1)	(2)	(3)	(4)	(5)	(6)
	Drop Dropouts	Drop Aug.2003 PG&E	Drop Dropouts	Drop Aug.2003 PG&E	Drop Dropouts	Drop Aug.2003 PG&E
T=1: CPP T=0: TOU	D = Number of critical peak days so far		D = Number of critical peak days in week 1		D = Peak temperature in week 1	
C ($b_{1,p}$)	0.488***	0.425***	0.323**	0.349**	0.385***	0.381***
	(0.158)	(0.156)	(0.159)	(0.161)	(0.134)	(0.136)
D ($b_{2,p}$)	0.0688*	0.0667*	0.0592	0.0848	0.0752***	0.0756***
	(0.0359)	(0.0356)	(0.0819)	(0.0812)	(0.0157)	(0.0158)
T * C ($b_{4,p}$)	-0.734***	-0.665***	-0.819***	-0.793***	-0.806***	-0.753***
	(0.198)	(0.195)	(0.203)	(0.205)	(0.168)	(0.170)
T * D ($b_{5,p}$)	-0.0869**	-0.0944**	-0.165*	-0.168*	-0.0303	-0.0292
	(0.0419)	(0.0416)	(0.0882)	(0.0882)	(0.0196)	(0.0193)
Summer Pricing	-0.0523	-0.0890	0.111	0.0711	0.0667	0.0542
	(0.0752)	(0.0781)	(0.0855)	(0.0859)	(0.0864)	(0.0871)
Peak Degree Hours	0.154***	0.156***	0.168***	0.169***	0.153***	0.155***
	(0.00807)	(0.00790)	(0.00865)	(0.00855)	(0.00751)	(0.00745)
Constant	3.993***	3.038***	3.754***	3.563***	3.304***	3.256***
	(0.127)	(0.131)	(0.150)	(0.161)	(0.188)	(0.193)
Day-of-week effects	Y	Y	Y	Y	Y	Y
Month-of-year effects	Y	Y	Y	Y	Y	Y
Household fixed effects	Y	Y	Y	Y	Y	Y
Daily Observations	150,206	155,893	116,469	118,598	116,469	118,598
R-squared (within)	0.143	0.144	0.159	0.158	0.165	0.164
Total Number of Households	801	894	798	884	798	884

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, *p<0.1

Note: Results of fixed-effect regressions exploring the correlation of daily peak kWh usage during a subsample of days in the experiment and a set of explanatory variables. The CPPL and CPPH treatment groups are pooled and the TOU group is used as the counterfactual. These regressions are reproductions of those presented in Table 1.5. Columns (1), (3) and (5) present the results of the regressions after the households that dropped out of the experiment partway through have been dropped. Columns (2), (4) and (6) present the results of the regressions after days in August 2003 for PG&E households have been dropped.

Appendix A.3: Proof of Roy's Identity in this simple case

Recall the value function in it's complete original form, where $\delta = \eta$ in the case of a gain and $\delta = \eta\lambda$ in the case of a loss, is:

$U(y_{op}, y_p, z; p_r) = u(y_{op}, y_p) + z + \delta y_p (p_p - p_r) + \delta y_{op} (p_{op} - p_r)$

The budget constraint is: $I = y_{op} p_{op} + y_p p_p + z$

Therefore the optimization problem is:

$$\max_{y_{op}, y_p, z} U(y_{op}, y_p, z; p_r) = u(y_{op}, y_p) + z - \delta y_p (p_p - p_r) - \delta y_{op} (p_{op} - p_r)$$
$$s.t.\ I = y_{op} p_{op} + y_p p_p + z$$

The Lagrangian is:

$$\mathcal{L}(y_{op}, y_p, z, \mu) = u(y_{op}, y_p) + z - \delta y_p (p_p - p_r) - \delta y_{op} (p_{op} - p_r) + \mu (I - y_{op} p_{op} - y_p p_p - z)$$

Given the assumption of the above functional form of the value function, I will prove, without loss of generality, that off the kink $y_p^* = \frac{-\frac{\partial V(\boldsymbol{p}, I; p_r)}{\partial \bar{p}_p}}{\frac{\partial V(\boldsymbol{p}, I; p_r)}{\partial I}}$.

Proof:

First I show that $\frac{\partial V(\boldsymbol{p}, I; p_r)}{\partial I} = 1$ (Note, it is not necessary that the marginal utility of income be equal to one, I make that simplifying assumption in my model, as utility can be scaled to any value).

Recall that **off the kink**, the first order conditions are:

$$\frac{\partial u(y_{op}, y_p)}{\partial y_{op}} - \delta (p_{op} - p_r) - \mu p_{op} = 0 \quad (1)$$
$$\frac{\partial u(y_{op}, y_p)}{\partial y_p} - \delta (p_p - p_r) - \mu p_p = 0 \quad (2)$$
$$\frac{\partial z}{\partial z} - \mu = 0 \quad (3)$$
$$I - y_{op} p_{op} - y_p p_p - z = 0 \quad (4)$$

First, by Equation 3 we see that $\mu = 1$ and from Equation 4 $z = I - y_{op} p_{op} - y_p p_p$. Additionally, recall that by definition $\bar{p}_j = p_j + \delta (p_j - p_r)$. Therefore to simplify the problem, return to the original optimization and re-write the problem substituting in these three features:

$$\max_{y_{op}, y_p} U(y_{op}, y_p; p_r) = u(y_{op}, y_p) - y_p \bar{p}_p - y_{op} \bar{p}_{op}$$

The first order conditions to this simplified problem are:

$$\frac{\partial U\left(y_{op}, y_p; p_r\right)}{\partial y_{op}} - p_{op} = \frac{\partial u\left(\boldsymbol{y}\right)}{\partial y_{op}} - \bar{p}_{op} = 0 \tag{5}$$

$$\frac{\partial U\left(y_{op}, y_p; p_r\right)}{\partial y_p} - p_p = \frac{\partial u\left(\boldsymbol{y}\right)}{\partial y_p} - \bar{p}_p = 0 \tag{6}$$

From this we see that both y_{op}^* and y_p^* will both be functions of $\bar{p}_{op}$ and $\bar{p}_p$, therefore so too will the indirection utility be a function of $\bar{p}_{op}$ and $\bar{p}_p$. This is because by definition $V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right) = U\left(y_{op}^*, y_p^*; p_r\right)$

Therefore

$$\frac{\partial V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)}{\partial I} = \frac{\partial U\left(y_{op}, y_p, z; p_r\right)}{\partial y_{op}} \frac{y_{op}^*}{\partial I} + \frac{\partial U\left(y_{op}, y_p, z; p_r\right)}{\partial y_p} \frac{y_p^*}{\partial I} + \frac{\partial U\left(y_{op}, y_p, z; p_r\right)}{\partial z} \frac{\partial z^*}{\partial I} \tag{7}$$

Then, by the first order conditions, and from the fact that $\frac{\partial U\left(y_{op}, y_p, z; p_r\right)}{\partial z} = 1$ because $U\left(y_{op}, y_p, z; p_r\right) = u\left(y_{op}, y_p\right) + z - \delta y_p\left(p_p - p_r\right) - \delta y_{op}\left(p_{op} - p_r\right)$:

$$\frac{\partial V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)}{\partial I} = p_{op} \frac{\partial y_{op}^*}{\partial I} + p_p \frac{\partial y_p^*}{\partial I} + \frac{\partial z^*}{\partial I} \tag{8}$$

Differentiating both sides of budget constraint by I we know:

$$p_{op} \frac{\partial y_{op}^*}{\partial I} + p_p \frac{\partial y_p^*}{\partial I} + \frac{\partial z^*}{\partial I} = 1 \tag{9}$$

Therefore combining Equations 8 and 9 we get that:

$$\frac{\partial V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)}{\partial I} = 1$$

Now, note: $\frac{\partial \bar{p}_p}{p_p} = (1 + \delta)$

Differentiate $V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)$ with respect to p_p, (recall that $\partial U\left(y_{op}, y_p, z; p_r\right)$ is both a function of $y_p^*\left(\bar{p}_p\left(p_p\right)\right)$, and of p_p directly):

$$\begin{aligned}
\frac{\partial V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)}{\partial p_p} =& \frac{\partial U\left(y_{op}, y_p, z; p_r\right)}{\partial y_{op}} \frac{\partial y_{op}^*}{\partial \bar{p}_p} \frac{\partial \bar{p}_p}{\partial p_p} \\
&+ \left[\frac{\partial U\left(y_{op}, y_p, z; p_r\right)}{\partial y_p} \frac{\partial y_p^*}{\partial \bar{p}_p} \frac{\partial \bar{p}_p}{\partial p_p} + \frac{\partial U\left(y_{op}, y_p, z; p_r\right)}{\partial p_p}\right] \\
&+ \frac{\partial U\left(y_{op}, y_p, z; p_r\right)}{\partial z} \frac{\partial z^*}{\partial \bar{p}_p} \frac{\partial \bar{p}_p}{\partial p_p} \\
=& p_{op} \frac{\partial y_{op}^*}{\partial \bar{p}_p}(1 + \delta) + p_p \frac{\partial y_p^*}{\partial \bar{p}_p}(1 + \delta) + \delta y_p^* + \frac{\partial z^*}{\partial \bar{p}_p}(1 + \delta)
\end{aligned} \tag{10}$$

And differentiate both sides of the budget constraint with respect to p_p:

$$p_{op} \frac{\partial y_{op}^*}{\partial \bar{p}_p}(1 + \delta) + p_p \frac{\partial y_p^*}{\partial \bar{p}_p}(1 + \delta) + y_p^* + \frac{\partial z^*}{\partial \bar{p}_p}(1 + \delta) = 0 \tag{11}$$

Therefore, combining Equations 10 and 11:

$$-y_p^* = \frac{\partial V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)}{\partial p_p} - \delta y_p^*$$

Therefore (assuming $\delta \neq -1$, which is true based on the assumption that $\eta \geq 0$ and $\lambda \geq 1$), then:

$$y_p^* = -\frac{\partial V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)}{\partial p_p}\frac{1}{(1+\delta)} = -\frac{\frac{\partial V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)}{\partial p_p}}{\frac{\partial V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)}{\partial I}}\frac{1}{(1+\delta)}$$

Therefore

$$y_p^* \neq -\frac{\frac{\partial V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)}{\partial p_p}}{\frac{\partial V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)}{\partial I}}$$

So Roy's Identity does not hold with respect to p_p. However, note that:

$$\frac{\partial V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)}{\partial \bar{p}_p} = \frac{\partial V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)}{\partial p_p}\frac{\partial p_p}{\partial \bar{p}_p} = \frac{\partial V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)}{\partial p_p}\frac{1}{\frac{\partial \bar{p}_p}{\partial p_p}} = \frac{\partial V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)}{\partial p_p}\frac{1}{(1+\delta)}$$

Therefore, in this model, off the kink the following is a true statement, and the equivalent relationship in this case to the more standard Roy's Identity:

$$y_p^* = -\frac{\frac{\partial V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)}{\partial \bar{p}_p}}{\frac{\partial V\left(I, \bar{p}_{op}, \bar{p}_p; p_r\right)}{\partial I}}$$

■

Appendix A.4: Parametric value function and maximization problem

$$
\begin{aligned}
\max_{y_{op},y_p,z} U(\boldsymbol{y}, z; \boldsymbol{x}, r) =& \mu z + \frac{\left(\beta_{op}\alpha_p^2 + \beta_p\alpha_{op}^2 - 2\gamma\alpha_{op}\alpha_p\right)}{2\left(\beta_{op}\beta_p - \gamma^2\right)} \\
&+ \frac{\mu\left(\alpha_p\gamma - \alpha_{op}\beta_p\right)}{\left(\beta_{op}\beta_p - \gamma^2\right)} y_{op} + \frac{\mu\left(\alpha_{op}\gamma - \alpha_p\beta_{op}\right)}{\left(\beta_{op}\beta_p - \gamma^2\right)} y_p \\
&- \frac{\left(\gamma\alpha_p\theta_{op} - \beta_p\alpha_{op}\theta_{op}\right)}{\left(\beta_{op}\beta_p - \gamma^2\right)} x_{op} - \frac{\left(\gamma\alpha_{op}\theta_p - \beta_{op}\alpha_p\theta_p\right)}{\left(\beta_{op}\beta_p - \gamma^2\right)} x_p \\
&+ \frac{\mu^2\beta_p}{2\left(\beta_{op}\beta_p - \gamma^2\right)} y_{op}^2 + \frac{\mu^2\beta_{op}}{2\left(\beta_{op}\beta_p - \gamma^2\right)} y_p^2 \\
&+ \frac{\beta_{op}\theta_p^2}{2\left(\beta_{op}\beta_p - \gamma^2\right)} x_p^2 + \frac{\beta_p\theta_{op}^2}{2\left(\beta_{op}\beta_p - \gamma^2\right)} x_{op}^2 \\
&- \frac{\mu\theta_{op}\beta_p}{\left(\beta_{op}\beta_p - \gamma^2\right)} y_{op}x_{op} + \frac{\mu\theta_p\gamma}{\left(\beta_{op}\beta_p - \gamma^2\right)} y_{op}x_p \\
&- \frac{\mu\theta_2\beta_{op}}{\left(\beta_{op}\beta_p - \gamma^2\right)} y_p x_p + \frac{\mu\theta_{op}\gamma}{\left(\beta_{op}\beta_p - \gamma^2\right)} y_p x_{op} \\
&- \frac{\gamma\theta_p\theta_{op}}{\left(\beta_{op}\beta_p - \gamma^2\right)} x_{op}x_p - \frac{\mu^2\gamma}{\left(\beta_{op}\beta_p - \gamma^2\right)} y_{op}, y_p \\
&- \lambda\eta\left(p_{op}y_{op} + p_p y_p - p_r y_{op} - p_r y_p\right)
\end{aligned}
$$

Subject to: $p_{op}y_{op} + p_p y_p + z = I$
Transformed into an unconstrained problem:

$$
\begin{aligned}
\max_{y_{op},y_p} U\left(\boldsymbol{y};\boldsymbol{x},r\right) =& \mu\left(I - p_{op}y_{op} - p_p y_p\right) + \frac{\left(\beta_{op}\alpha_p^2 + \beta_p\alpha_{op}^2 - 2\gamma\alpha_{op}\alpha_p\right)}{2\left(\beta_{op}\beta_p - \gamma^2\right)} \\
&+ \frac{\mu\left(\alpha_p\gamma - \alpha_{op}\beta_p\right)}{\left(\beta_{op}\beta_p - \gamma^2\right)}y_{op} + \frac{\mu\left(\alpha_{op}\gamma - \alpha_p\beta_{op}\right)}{\left(\beta_{op}\beta_p - \gamma^2\right)}y_p \\
&- \frac{\left(\gamma\alpha_p\theta_{op} - \beta_p\alpha_{op}\theta_{op}\right)}{\left(\beta_{op}\beta_p - \gamma^2\right)}x_{op} - \frac{\left(\gamma\alpha_{op}\theta_p - \beta_{op}\alpha_p\theta_p\right)}{\left(\beta_{op}\beta_p - \gamma^2\right)}x_p \\
&+ \frac{\mu^2\beta_p}{2\left(\beta_{op}\beta_p - \gamma^2\right)}y_{op}^2 + \frac{\mu^2\beta_{op}}{2\left(\beta_{op}\beta_p - \gamma^2\right)}y_p^2 \\
&+ \frac{\beta_{op}\theta_p^2}{2\left(\beta_{op}\beta_p - \gamma^2\right)}x_p^2 + \frac{\beta_p\theta_{op}^2}{2\left(\beta_{op}\beta_p - \gamma^2\right)}x_{op}^2 \\
&- \frac{\mu\theta_{op}\beta_p}{\left(\beta_{op}\beta_p - \gamma^2\right)}y_{op}x_{op} + \frac{\mu\theta_p\gamma}{\left(\beta_{op}\beta_p - \gamma^2\right)}y_{op}x_p \\
&- \frac{\mu\theta_2\beta_{op}}{\left(\beta_{op}\beta_p - \gamma^2\right)}y_p x_p + \frac{\mu\theta_{op}\gamma}{\left(\beta_{op}\beta_p - \gamma^2\right)}y_p x_{op} \\
&- \frac{\gamma\theta_p\theta_{op}}{\left(\beta_{op}\beta_p - \gamma^2\right)}x_{op}x_p - \frac{\mu^2\gamma}{\left(\beta_{op}\beta_p - \gamma^2\right)}y_{op}y_p \\
&- \lambda\eta\left(p_{op}y_{op} + p_p y_p - p_r y_{op} - p_r y_p\right)
\end{aligned}
$$

First order Conditions:

$$
\begin{aligned}
FOC\ wrt\ y_{op}:& \frac{\mu\left(\alpha_p\gamma - \alpha_{op}\beta_p\right)}{\left(\beta_{op}\beta_p - \gamma^2\right)} + \frac{\mu^2\beta_p}{\left(\beta_{op}\beta_p - \gamma^2\right)}y_{op} - \frac{\mu\theta_{op}\beta_p}{\left(\beta_{op}\beta_p - \gamma^2\right)}x_{op} \\
&+ \frac{\mu\theta_p\gamma}{\left(\beta_{op}\beta_p - \gamma^2\right)}x_p - \frac{\mu^2\gamma}{\left(\beta_{op}\beta_p - \gamma^2\right)}y_p - \lambda\eta\left(p_{op} - p_r\right) - \mu p_{op} = 0 \\
FOC\ wrt\ y_p:& \frac{\mu\left(\alpha_{op}\gamma - \alpha_p\beta_{op}\right)}{\left(\beta_{op}\beta_p - \gamma^2\right)} + \frac{\mu^2\beta_{op}}{\left(\beta_{op}\beta_p - \gamma^2\right)}y_p - \frac{\mu\theta_2\beta_{op}}{\left(\beta_{op}\beta_p - \gamma^2\right)}x_p \\
&+ \frac{\mu\theta_{op}\gamma}{\left(\beta_{op}\beta_p - \gamma^2\right)}x_{op} - \frac{\mu^2\gamma}{\left(\beta_{op}\beta_p - \gamma^2\right)}y_{op} - \lambda\eta\left(p_p - p_r\right) - \mu p_p = 0
\end{aligned}
$$

Solve for y_{op} and y_p (where $\bar{p}_p = \mu p_p + \lambda\eta\left(p_p - p_r\right)$ and $\bar{p}_{op} = \mu p_{op} + \lambda\eta\left(p_{op} - p_r\right)$):

$$
\begin{aligned}
y_{op}^*\left(\bar{\boldsymbol{p}},\boldsymbol{x}\right) &= \frac{\alpha_{op}}{\mu} + \frac{\theta_{op}}{\mu}x_{op} + \frac{\beta_{op}}{\mu}\bar{p}_{op} + \frac{\gamma}{\mu}\bar{p}_p \\
y_p^*\left(\bar{\boldsymbol{p}},\boldsymbol{x}\right) &= \frac{\alpha_p}{\mu} + \frac{\theta_p}{\mu}x_p + \frac{\beta_p}{\mu}\bar{p}_p + \frac{\gamma}{\mu}\bar{p}_{op}
\end{aligned}
$$

Plug back into value function and solve:

$$
V\left(\bar{\boldsymbol{p}},\bar{I}\right) = \mu\bar{I} - \alpha_{op}\bar{p}_{op} - \theta_{op}x_{op}\bar{p}_{op} - \alpha_p\bar{p}_p - \theta_p w_p\bar{p}_p - \frac{\beta_{op}}{2}\bar{p}_{op}^2 - \frac{\beta_p}{2}\bar{p}_p^2 - \gamma\bar{p}_{op}\bar{p}_p
$$

Appendix A.5: Alternate Hypotheses Regressions with TOU as Counterfactual

Table A.4: Learning vs Loss Aversion: CPP vs TOU

Dependent Variable: Peak kWh									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T=1: CPP T=0: TOU	D = Number of critical peak days so far			D = Number of critical peak days in week 1			D = Peak temerature in week 1		
	Original	E = overall number of critical days so far		Original	E = overall number of critical days so far		Original	E = overall number of critical days so far	
C ($b_{1,p}$)	0.442***	0.426***	0.411***	0.300*	0.301**	0.278*	-0.777***	0.365***	0.349***
	(0.152)	(0.153)	(0.149)	(0.155)	(0.152)	(0.144)	(0.163)	(0.129)	(0.128)
D ($b_{2,p}$)	0.0704**	0.0839**	0.0705**	0.0662	0.0688	0.0352	-0.0294	0.0748***	0.0730***
	(0.0354)	(0.0326)	(0.0292)	(0.0797)	(0.0770)	(0.0802)	(0.0190)	(0.0151)	(0.0156)
T * C ($b_{4,p}$)	-0.690***	-0.686***	-0.674***	-0.789***	-0.787***	-0.761***	-0.777***	-0.774***	-0.755***
	(0.191)	(0.192)	(0.186)	(0.196)	(0.192)	(0.181)	(0.163)	(0.160)	(0.158)
T * D ($b_{5,p}$)	-0.0851**	-0.0865**	-0.0705**	-0.170**	-0.167**	-0.127	-0.0294	-0.0296	-0.0267
	(0.0412)	(0.0386)	(0.0341)	(0.0863)	(0.0830)	(0.0873)	(0.0190)	(0.0188)	(0.0198)
E		-0.0110	-0.0272		-0.00150	-0.0145		-0.00664	-0.00869
		(0.00861)	(0.0302)		(0.0107)	(0.0412)		(0.0107)	(0.0406)
E^2			0.000589			0.000468			0.00006
			(0.00112)			(0.00145)			(0.00137)
T * E		0.00222	0.0380		-0.00161	0.0486		-0.000197	0.0386
		(0.0101)	(0.0338)		(0.0128)	(0.0453)		(0.0126)	(0.0440)
T * E^2			-0.00144			-0.00198			-0.00155
			(0.00124)			(0.00166)			(0.00152)
Summer Pricing	-0.0894	-0.0913	-0.0895	0.0706	0.0704	0.0731	0.0308	0.0305	0.0326
	(0.0768)	(0.0768)	(0.0768)	(0.0848)	(0.0847)	(0.0850)	(0.0857)	(0.0857)	(0.0860)
Peak Degree Hours	0.155***	0.155***	0.155***	0.170***	0.170***	0.170***	0.155***	0.155***	0.155***
	(0.00783)	(0.00783)	(0.00784)	(0.00838)	(0.00838)	(0.00837)	(0.00729)	(0.00729)	(0.00727)
Constant	3.996***	4.109***	3.241***	3.758***	3.790***	2.989***	3.302***	3.384***	2.308***
	(0.128)	(0.137)	(0.165)	(0.148)	(0.156)	(0.194)	(0.183)	(0.187)	(0.244)
Day-of-week effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-of-year effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Household fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Daily Observations	159,244	159,244	159,244	123,564	123,564	123,564	123,564	123,564	123,564
R-squared (within)	0.143	0.143	0.143	0.159	0.159	0.159	0.165	0.165	0.165
Number of Households	906	906	906	892	892	892	892	892	892

Standard errors clustered at household level in parentheses
*** p<0.01, ** p<0.05, *p<0.1

Note: Results of fixed-effect regressions exploring the correlation of daily peak kWh usage during a subsample of days in the experiment and a set of explanatory variables. The CPPL and CPPH treatment groups are pooled and the TOU group is used as the counterfactual. Columns (1), (4) and (7) reproduce the results of the original specifications from Table 1.5, columns (2), (5) and (8) control for the total number of critical peak days experienced in the pilot overall (E), and columns (3), (6) and (9) allow this variable to enter quadratically.

Table A.5: Budget Constrained vs Loss Aversion: CPP vs TOU

Dependent Variable: Peak kWh						
	(1)		(2)		(3)	
T=1: CPP T=0: TOU	D = Number of critical peak days so far		D = Number of critical peak days in week 1		D = Peak temerature in week 1	
C * (Income<25,000)	0.331	(0.359)	0.172	(0.342)	0.295	(0.281)
C * (25,000<Income<50,000)	0.579	(0.363)	0.437	(0.347)	0.545*	(0.295)
C * (50,000<Income<75,000)	-0.00140	(0.298)	-0.0669	(0.361)	-0.00755	(0.318)
C * (75,000<Income<100,000)	0.916*	(0.506)	0.575	(0.521)	0.757	(0.496)
C * (100,000<Income<150,000)	1.324*	(0.801)	1.016	(0.747)	1.047*	(0.597)
C * (150,000<Income)	-0.538*	(0.324)	-0.604*	(0.351)	-0.416	(0.344)
D * (Income<25,000)	0.0371	(0.0687)	-0.0410	(0.111)	0.0418	(0.0290)
D * (25,000<Income<50,000)	0.0855	(0.0689)	0.148	(0.174)	0.0535**	(0.0261)
D * (50,000<Income<75,000)	0.149*	(0.0874)	0.327*	(0.196)	0.0943**	(0.0393)
D * (75,000<Income<100,000)	0.174*	(0.103)	0.350*	(0.206)	0.0826***	(0.0246)
D * (100,000<Income<150,000)	0.111	(0.140)	0.00830	(0.354)	0.189**	(0.0924)
D * (150,000<Income)	-0.117	(0.0919)	-0.392***	(0.129)	-0.00506	(0.0167)
T * C * (Income<25,000)	-0.512	(0.412)	-0.667*	(0.381)	-0.666**	(0.309)
T * C * (25,000<Income<50,000)	-1.223***	(0.401)	-1.140***	(0.395)	-1.116***	(0.339)
T * C * (50,000<Income<75,000)	-0.108	(0.421)	-0.389	(0.472)	-0.401	(0.394)
T * C * (75,000<Income<100,000)	-1.176**	(0.551)	-0.986*	(0.572)	-1.040*	(0.540)
T * C * (100,000<Income<150,000)	-0.781	(0.897)	-1.084	(0.826)	-1.389**	(0.670)
T * C * (150,000<Income)	0.154	(0.464)	-0.0344	(0.502)	-0.209	(0.463)
T * D * (Income<25,000)	-0.0488	(0.0778)	-0.0547	(0.130)	-0.0138	(0.0329)
T * D * (25,000<Income<50,000)	-0.0974	(0.0793)	-0.263	(0.191)	-0.0228	(0.0312)
T * D * (50,000<Income<75,000)	-0.113	(0.102)	-0.329	(0.230)	-0.0353	(0.0490)
T * D * (75,000<Income<100,000)	-0.180	(0.114)	-0.473**	(0.227)	-0.0496	(0.0329)
T * D * (100,000<Income<150,000)	0.0216	(0.164)	0.228	(0.395)	-0.0292	(0.0994)
T * D * (150,000<Income)	-0.0683	(0.117)	-0.160	(0.191)	0.0480	(0.0385)
Summer Pricing	-0.118	(0.0802)	0.0882	(0.0902)	0.0435	(0.0922)
Peak Degree Hours	0.154***	(0.00840)	0.170***	(0.00886)	0.155***	(0.00757)
Constant	2.994***	(0.140)	3.326***	(0.120)	2.803***	(0.153)
Day-of-week effects	Y		Y		Y	
Month-of-year effects	Y		Y		Y	
Household fixed effects	Y		Y		Y	
Daily Observations	140,903		109,515		109,515	
R-squared (within)	0.145		0.162		0.173	
Total Number of Households	748		739		739	

Standard errors clustered at household level in parentheses
*** p<0.01, ** p<0.05, *p<0.1

Note: Results of fixed-effect regressions exploring the correlation of daily peak kWh usage during a subsample of days in the experiment and a set of explanatory variables. The CPPL and CPPH treatment groups are pooled and the TOU group is used as the counterfactual. Results are differentiated across six income brackets. The analysis is limited to households who provided answers to the income question in the survey (83% of CPP households and 84% of TOU households).

Table A.6: Artificially Shifted Bill Periods: CPP vs TOU

Dependent Variable: Peak kWh						
T=1: CPP T=0: TOU	(1) D = Number of critical peak days so far	(2)	(3) D = Number of critical peak days in week 1	(4)	(5) D = Peak temerature in week 1	(6)
	Original	Shift bill period by two weeks	Original	Shift bill period by two weeks	Original	Shift bill period by two weeks
C ($b_{1,p}$)	0.442***	0.513***	0.300*	0.309**	-0.777***	0.327**
	(0.152)	(0.157)	(0.155)	(0.157)	(0.163)	(0.131)
D ($b_{2,p}$)	0.0704**	0.0228	0.0662	0.0741	-0.0294	0.0763***
	(0.0354)	(0.0322)	(0.0797)	(0.0759)	(0.0190)	(0.0153)
T * C ($b_{4,p}$)	-0.690***	-0.743***	-0.789***	-0.867***	-0.777***	-0.823***
	(0.191)	(0.196)	(0.196)	(0.201)	(0.163)	(0.167)
T * D ($b_{5,p}$)	-0.0851**	-0.0555	-0.170**	-0.133	-0.0294	-0.0347*
	(0.0412)	(0.0377)	(0.0863)	(0.0831)	(0.0190)	(0.0195)
Summer Pricing	-0.0894	-0.0898	0.0706	0.0640	0.0308	0.0514
	(0.0768)	(0.0768)	(0.0848)	(0.0895)	(0.0857)	(0.0913)
Peak Degree Hours	0.155***	0.155***	0.170***	0.170***	0.155***	0.155***
	(0.00783)	(0.00783)	(0.00838)	(0.00837)	(0.00729)	(0.00754)
Constant	3.996***	3.995***	3.758***	3.421***	3.302***	2.942***
	(0.128)	(0.128)	(0.148)	(0.117)	(0.183)	(0.150)
Day-of-week effects	Y	Y	Y	Y	Y	Y
Month-of-year effects	Y	Y	Y	Y	Y	Y
Household fixed effects	Y	Y	Y	Y	Y	Y
Daily Observations	159,244	159,244	123,564	110,934	123,564	110,934
R-squared (within)	0.143	0.143	0.159	0.162	0.165	0.167
Number of Households	906	906	892	895	892	895

Standard errors clustered at household level in parentheses

*** p<0.01, ** p<0.05, *p<0.1

Note: Results of fixed-effect regressions exploring the correlation of daily peak kWh usage during a subsample of days in the experiment and a set of explanatory variables. The CPPL and CPPH treatment groups are pooled and the TOU group is used as the counterfactual. Columns (1), (3) and (5) reproduce the results of the original specifications from Table 1.5, columns (2), (4) and (6) show the results after the definition of the bill period has been artificially shifted back 14 days for each bill period for each household.

Appendix B: Appendices for Chapter 2

Appendix B.1: Detailed Derivation of Model with Three Consumer Types

Assume consumers have unit demand for a good. Assume there are multiple models of clothes washers provided by the monopolist, indexed by j, which vary over efficiency level (e_j) and price (p_j). Assume there are three types of consumers – high 1, middle 2, and low 3 – that have a high, mid-range, and low willingness to pay for efficiency, respectively; assume θ^k is the valuation of consumer type k for efficiency e_j of model j where, without loss of generality, $\theta^3 < \theta^2 < \theta^1$. Utility of consumer i for model j is:

$$\begin{aligned} U_{kj} &= \theta^k e_j - p_j \\ \text{where:}& \\ \theta^k \in \{\theta^3, \theta^2, \theta^1\} &= \text{valuation of energy efficiency } e \text{ of the three consumer types} \\ e_j &= \text{energy efficiency level of model } j \\ p_j &= \text{purchase price of model } j \end{aligned}$$

Suppose there are N consumers and $s_3 N$ have valuation θ^3, $s_2 N$ have valuation θ^2, and $s_1 N$ have valuation θ^1, where $\sum_{k=1}^{3} s_k = 1$. The monopolist does not observe a consumer's type, so they cannot perfectly price discriminate. Assume the cost of producing energy efficiency level e_j is $c(e_j)$, and that $c(e_j) \geq 0$, $c'(e_j) \geq 0$ and $c''(e_j) > 0$.

Social Welfare Maximizing (Perfectly Competitive) Case:

A social planner would choose the efficiency levels to maximize total welfare (averaged over the population with weights based on the distribution of types in the population). They would therefore solve the optimization problem presented in Equation 1.

$$\max_{e_1, e_2, e_3} W = s_3 \cdot \left(\theta^3 e_3 - c(e_3)\right) + s_2 \cdot \left(\theta^2 e_2 - c(e_2)\right) + s_1 \cdot \left(\theta^1 e_1 - c(e_1)\right) \tag{1}$$

The first order conditions for the social planner are shown in Equation System 2.

$$\begin{aligned} c'(e_3^*) &= \theta^3 \\ c'(e_2^*) &= \theta^2 \\ c'(e_1^*) &= \theta^1 \end{aligned} \tag{2}$$

While in this case consumer demand is perfectly inelastic, in a perfectly competitive setting with free entry of firms, price above marginal cost would result in excess supply. Therefore the optimal prices are also equal to marginal cost for the social welfare maximizing case. This result is shown in Equation System 3.

$$
\begin{aligned}
c'\left(e_3^*\right) &= p^{3*} \\
c'\left(e_2^*\right) &= p^{2*} \\
c'\left(e_1^*\right) &= p^{1*}
\end{aligned} \tag{3}
$$

Monopolist Second-Degree Price Discrimination Case:

The monopolist solves the problem in Equation 4 in order to choose the efficiency levels and prices of the three types of models they supply. The $IR1$, $IR2$ and $IR3$ constraints refer to the IR constraint for the high, middle, and low type of consumer, respectively. The ICj_k constraint refer to the constraint assuring that consumer type j will be unwilling to purchase product type $k \neq j$ in equilibrium.

$$
\begin{aligned}
\max_{p_1,p_2,p_3,e_1,e_2,e_3} \; & \pi = s_3 \cdot (p_3 - c\left(e_3\right)) + s_2 \cdot (p_2 - c\left(e_2\right)) + s_1 \cdot (p_1 - c(e_1)) \\
s.t.& \\
IR1 :& \theta^1 e_1 - p_1 \geq 0 \\
IR2 :& \theta^2 e_2 - p_2 \geq 0 \\
IR3 :& \theta^3 e_3 - p_3 \geq 0 \\
IC1_2 :& \theta^1 e_1 - p_1 \geq \theta^1 e_2 - p_2 \\
IC1_3 :& \theta^1 e_1 - p_1 \geq \theta^1 e_3 - p_3 \\
IC2_1 :& \theta^2 e_2 - p_2 \geq \theta^2 e_1 - p_1 \\
IC2_3 :& \theta^2 e_2 - p_2 \geq \theta^2 e_3 - p_3 \\
IC3_1 :& \theta^3 e_3 - p_3 \geq \theta^3 e_1 - p_1 \\
IC3_2 :& \theta^3 e_3 - p_3 \geq \theta^3 e_2 - p_2
\end{aligned} \tag{4}
$$

In a separating equilibrium (i.e. $p_j \neq p_k$ and $e_j \neq e_k$ $\forall j \neq k$) then $\theta^1 > \theta^2 > \theta^3$ implies that $IR3$, $IC1_2$ and $IC2_3$ are binding while $IR1$, $IR2$ $IC1_3$, $IC2_1$, $IC3_1$ and $IC3_2$ are all non-binding.[32] Therefore the original problem from Equation 4 simplifies to the problem in Equation 5.

$$
\begin{aligned}
\max_{p_1,p_2,p_3,e_1,e_2,e_3} \; & \pi = s_3 \cdot (p_3 - c\left(e_3\right)) + s_2 \cdot (p_2 - c\left(e_2\right)) + s_1 \cdot (p_1 - c(e_1)) \\
s.t.& \\
IR3 :& \theta^3 e_3 - p_3 = 0 \\
IC1_2 :& \theta^1 e_1 - p_1 = \theta^1 e_2 - p_2 \\
IC2_3 :& \theta^2 e_2 - p_2 = \theta^2 e_3 - p_3
\end{aligned} \tag{5}
$$

Solving for p_1, p_2 and p_3 from the constraints and plugging back into the objective function, the problem simplifies further to that in Equation 6.

[32] I provide the proof of this in Appendix B.2.

$$\begin{aligned}\max_{e_1,e_2,e_3} \pi =& s_3 \cdot \Big(\theta^3 e_3 - c\left(e_3\right)\Big) \\ &+ s_2 \cdot \Big(\theta^2\left(e_2 - e_3\right) + \theta^3 e_3 - c\left(e_2\right)\Big) \\ &+ s_1 \cdot \Big(\theta^1\left(e_1 - e_2\right) + \theta^2\left(e_2 - e_3\right) + \theta^3 e_3 - c(e_1)\Big)\end{aligned} \tag{6}$$

The first order conditions to this problem are shown in Equation System 7.

$$\begin{aligned} s_3 \cdot \Big(\theta^3 - c'\left(e_3\right)\Big) - s_2 \cdot \Big(\theta^2 - \theta^3\Big) - s_1 \cdot \Big(\theta^2 - \theta^3\Big) &= 0 \\ s_2 \cdot \Big(\theta^2 - c'\left(e_2\right)\Big) - s_1 \cdot \Big(\theta^1 - \theta^2\Big) &= 0 \\ s_1 \cdot \Big(\theta^1 - c'(e_1)\Big) &= 0 \end{aligned} \tag{7}$$

Using these first order conditions and the binding constraints, the solution for the monopolist under this second-degree price discrimination setting $\left(\bar{e}_j, \bar{p}_j\right), \ \forall j \in \{1,2,3\}$ are presented in Equation System 8.

$$\begin{aligned} c'(\bar{e}_3) =& \theta^3 - \frac{s_1 + s_2}{s_3}\Big(\theta^2 - \theta^3\Big) \\ c'\left(\bar{e}_2\right) =& \theta^2 - \frac{s_1}{s_2}\Big(\theta^1 - \theta^2\Big) \\ c'(\bar{e}_1) =& \theta^1 \\ \bar{p}_3 =& \theta^3 \bar{e}_3 \\ \bar{p}_2 =& \theta^3 \bar{e}_3 + \theta^2\left(\bar{e}_2 - \bar{e}_3\right) \\ \bar{p}_H =& \theta^3 \bar{e}_3 + \theta^2\left(\bar{e}_2 - \bar{e}_3\right) + \theta^1\left(\bar{e}_1 - \bar{e}_2\right) \end{aligned} \tag{8}$$

Monopoly Second-Degree Price Discrimination with Minimum Standard Case:

The new problem with the constraint that $e_j \geq e_3^*, \ \forall j \in \{1,2,3\}$, where this constraint is binding for type 3 products is presented in Equation 9.

$$\begin{aligned} \max_{p_1,p_2,p_3,e_1,e_2,e_3} & \pi = s_3 \cdot \left(p_3 - c\left(e_3\right)\right) + s_2 \cdot \left(p_2 - c\left(e_2\right)\right) + s_1 \cdot \left(p_1 - c(e_1)\right) \\ s.t.& \\ IR3 :& \theta^3 e_3 - p_3 = 0 \\ IC1_2 :& \theta^1 e_1 - p_1 = \theta^1 e_2 - p_2 \\ IC2_3 :& \theta^2 e_2 - p_2 = \theta^2 e_3 - p_3 \\ Standard :& e_3 = e_3^* \end{aligned} \tag{9}$$

Simplifying the problem further by plugging in the constraints, I get Equations 10.

$$\begin{aligned}\max_{e_2,e_1} \pi =& s_3 \cdot \Big(\theta^3 e_3^* - c\left(e_3^*\right)\Big) \\ &+ s_2 \cdot \Big(\theta^2\left(e_2 - e_3^*\right) + \theta^3 e_3^* - c\left(e_2\right)\Big) \\ &+ s_1 \cdot \Big(\theta^1\left(e_1 - e_2\right) + \theta^2\left(e_2 - e_3^*\right) + \theta^3 e_3^* - c(e_1)\Big)\end{aligned} \tag{10}$$

The first order conditions are shown in Equation System 11.

$$\begin{aligned}s_2 \cdot \Big(\theta^2 - c'\left(e_2\right)\Big) - s_1 \cdot \Big(\theta^1 - \theta^2\Big) = 0 \\ s_1 \cdot \Big(\theta^1 - c'(e_1)\Big) = 0\end{aligned} \tag{11}$$

Using these conditions and the rest of the binding constraints I can solve for the new monopoly menu of optimal price and efficiency levels given the standard, presented in Equation System 12.

$$\begin{aligned}c'(e_3^S) =& c'(e_3^*) = \theta^3 \\ c'\left(e_2^S\right) =& \theta^2 - \frac{s_1}{s_2}\left(\theta^1 - \theta^2\right) \\ c'(e_1^S) =& \theta^1 \\ p_3^S =& \theta^3 e_3^* \\ p_2^S =& \theta^3 e_3^* + \theta^2\left(e_2^S - e_3^*\right) \\ p_1^S =& \theta^3 e_3^* + \theta^2\left(e_2^S - e_3^*\right) + \theta^1\left(e_1^S - e_2^S\right)\end{aligned} \tag{12}$$

Appendix B.2: Binding Constraints in Price Discrimination Model

Proposition: In a separating equilibrium then $\theta^1 > \theta^2 > \theta^3$ implies that $IR3$, $IC1_2$ and $IC2_3$ are binding while $IR1$, $IR2$ $IC1_3$, $IC2_1$, $IC3_1$ and $IC3_2$ are all non-binding.

Proof:

1. ICj_k and ICk_j cannot both be binding $\forall j \neq k$ and $j, k \in \{1, 2, 3\}$:

   ICj_k and ICk_jboth binding

   By contradiction:

   $\theta^k e_k - p_k = \theta^k e_j - p_j$

   and $\theta^j e_j - p_j = \theta^j e_k - p_k$

   $\Rightarrow \theta^k = \frac{p_k - p_j}{(e_k - e_j)}$ (ok because assume $e_k \neq e_j$)

   and $\theta^j = \frac{p_k - p_j}{(e_k - e_j)}$

   $\Rightarrow \theta^k = \theta^j \boxtimes$

   Violates assumption that $\theta^k \neq \theta^j$, therefore ICj_k and ICk_j cannot both be binding.

2. If IRk is satisfied in equilibrium, then IRj $\forall j > k$ are satisfied in equilibrium.

   Directly: Assume IRk is satisfied

   $\theta^k e_k - p_k \geq 0$, and e_k and p_k are a feasible efficiency/price combination for the monopolist

   $\theta^j > \theta^k$ by assumption

   $\Rightarrow \theta^j e_k - p_k > 0$

   $\Rightarrow \exists\, (e_j, p_j) = (e_k, p_k)$ that is feasible for the monopolist, and $\theta^j e_j - p_j > 0$

   $\Rightarrow IRj$ is satisfied $\boxdot$

3. $IR3$ is binding

   By (2), if there is a type such that $\theta^j e_j - p_j \geq 0$ for that type j, then all higher types will thereby satisfy their IR constraints. The monopolist's profits are increasing in price and decreasing in efficiency level. They have an incentive to set price as high as possible and efficiency as low as possible. They will therefore set price and efficiency for this lowest feasible type j just such their IR constraint holds. Without loss of generality, call this lowest feasible type 3. Therefore $IR3$ is binding.

4. $IR2$ and $IR1$ are non-binding

   (a) By (3) $IR3$ is binding $\Rightarrow \theta^3 e_3 - p_3 = 0$

$IR1$ is non-binding:

$\theta^1 e_3 - p_3 > \theta^3 e_3 - p_3$ by $\theta^1 > \theta^3$

$IC1_3$ assures that: $\theta^1 e_1 - p_1 \geq \theta^1 e_3 - p_3$

$\Rightarrow \theta^1 e_1 - p_1 > 0$

$\Rightarrow IR1$ is non-binding

$IR_2$is non-binding:

Same proof as for $IR1$.

5. Either $IC1_3$ or $IC1_2$ is binding, and either $IC2_1$ or $IC2_3$ are binding.

   Either $IC1_3$ or $IC1_2$ is binding:

   By contradiction:

   From (4) $IR1$ is non-binding. If $IC1_3$ or $IC1_2$ are both non-binding as well, then $\theta^1 e_1 > p_1$ and $\theta^1 e_1 - \theta^1 e_3 + p_3 > p_1$ and $\theta^1 e_1 - \theta^1 e_2 + p_2 > p_1$ and $\exists \varepsilon$ s.t. $\theta^1 e_1 > p_1 + \varepsilon$ and $\theta^1 e_1 - \theta^1 e_3 + p_3 > p_1 + \varepsilon$ and $\theta^1 e_1 - \theta^1 e_2 + p_2 > p_1 + \varepsilon$. Then the monopoly could raise p_1 by ε (thereby increasing their profit) and have type θ^1 still be willing to be in the market and still purchase the type 1 product over the type 2 or 3 products, so the original p_1 can't have been an equilibrium price. ⊠

   Either $IC2_1$ or $IC2_3$ are binding: Same proof as for $IC1_3$ or $IC1_2$.

6. $IC1_3$ is non-binding:

   By contradiction:

   If not, then $\theta^1 e_1 - p_1 = \theta^1 e_3 - p_3$.

   $IC1_2$ assures us that $\theta^1 e_1 - p_1 \geq \theta^1 e_2 - p_2$

   Subtract $\theta^1 e_1 - p_1$ from the left-hand side of $IC1_2$ and subtract $\theta^1 e_3 - p_3$ from the right-hand side of $IC1_2$:

   $\Rightarrow 0 \geq \theta^1 (e_2 - e_3) - (p_2 - p_3)$

   $\Rightarrow \frac{(p_2 - p_3)}{(e_2 - e_3)} \geq \theta^1$ (taking as given that $e_2 > e_3$, which is the case in the solution to the problem).

   $\Rightarrow \frac{(p_2 - p_3)}{(e_2 - e_3)} > \theta^2$ by $\theta^1 > \theta^2$

   $\Rightarrow \theta^2 e_2 - p_2 < \theta^2 e_3 - p_3$ ⊠

   This contradicts the assumption that the $IC2_3$ must be satisfied. Therefore, $IC1_3$ is non-binding.

7. $IC1_2$ is binding

   By (4), (5) and (6)

8. $IC2_1$ is non-binding

   By (1) and (7)

9. $IC2_3$ is binding
   By (4), (5) and (8)
10. $IC3_2$ is non-binding
    by (1) and (9)

■

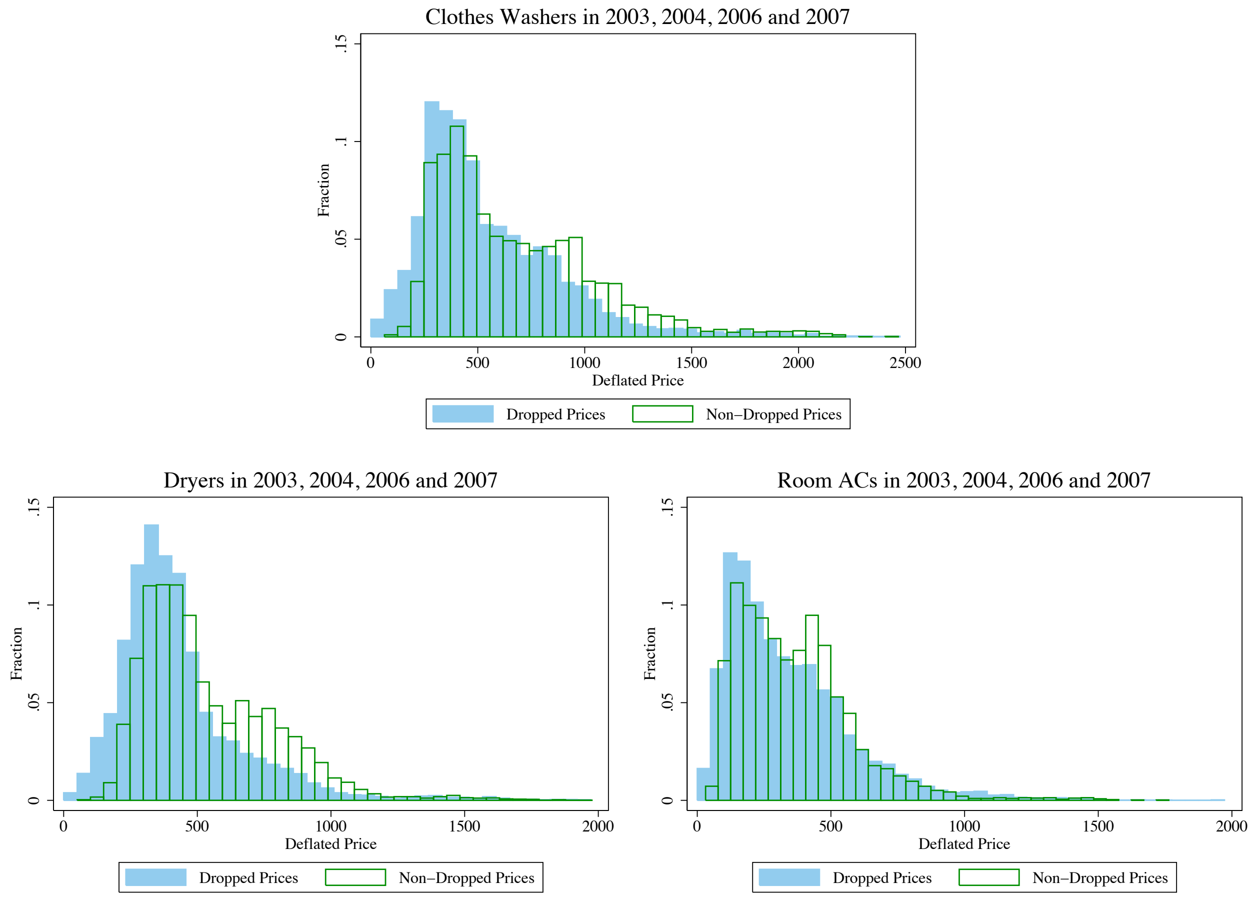
Appendix B.3: Retailers in NPD Data

Participating Retailers in NPD data:		Projected* Sales Included for:
Abt TV & Appliance	Kmart	ABC Warehouse
Amazon.com	Kohl's	BrandsMart
American TV	Linens 'n Things (Data thru 12/08)	Conn's Appliance
Bernies	Lowe's	Cowboy Maloney's
Best Buy	Macy's	Fry's
BJ's Wholesale Club	Meijer	Home Depot
Bloomingdale's	Nebraska Furniture Mart	Menards
Boscov's	PC Richard & Sons	Navy Exchange
Circuit City (Data thru 2/09)	Pamida	Queen City Appliance
Dillard's	RC Willey	REX Stores
Fortunoff (Data thru 5/09)	Sears	Vann's
Fred Meyer	Shopko	
Gottschalks (Data thru 3/09)	Target	
HH Gregg	Ultimate Electronics	
JC Penney		

* "Projected" refers to the fact that NPD included estimates of sales for this subset of retailers in their data. They claim that the share of overall market sales was no greater that 5% for all projected retailers combined for a given time period.

Appendix B.4: Comparison of Price Distributions of Included vs Omitted Data

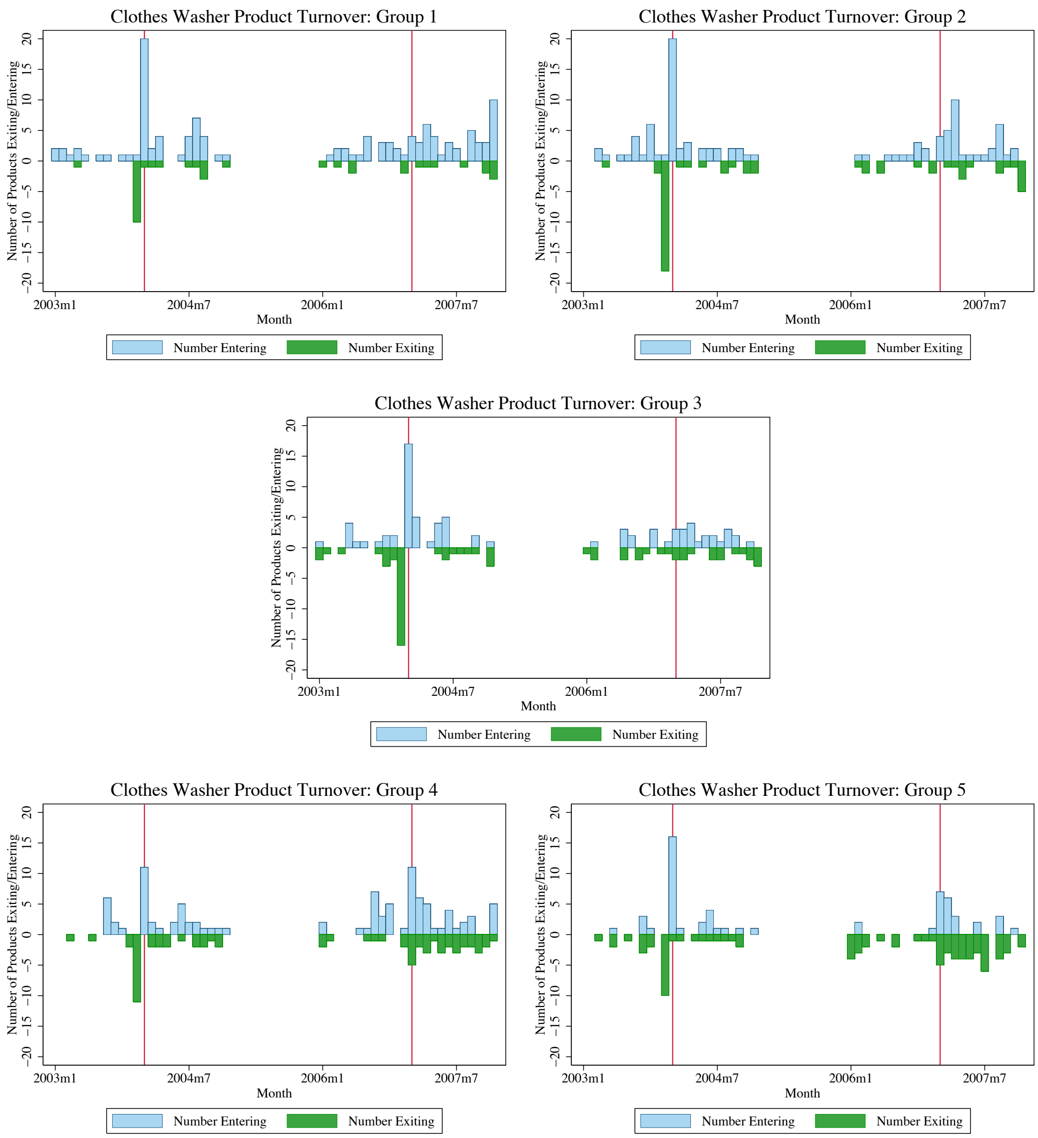
Figure B.1: Price Distribution of Included vs Omitted Data



Note: Distribution of the price (average revenue deflated using the CPI with base period December 2009) of data used in the full analysis in this paper (outlined histogram) and data omitted from the analysis (solid histogram). The top panel shows this comparison for clothes washers, the middle panel for dryers, and the bottom panel for room ACs. The data was omitted for clothes washers because it consists of model numbers that could not be matched to FTC energy usage data because the model numbers were masked in the NPD data. Similarly masked model numbers were dropped from the data for dryers and room ACs as well to maintain comparability of the subset of data used for each appliance. A smaller subset of data was additionally dropped for clothes washers because the model numbers did not appear in the FTC energy efficiency data.

Appendix B.5: Frequency of Models Exiting/Entering by Efficiency Group

Figure B.2: Model Entry and Exit From Market by Date and Efficiency Category

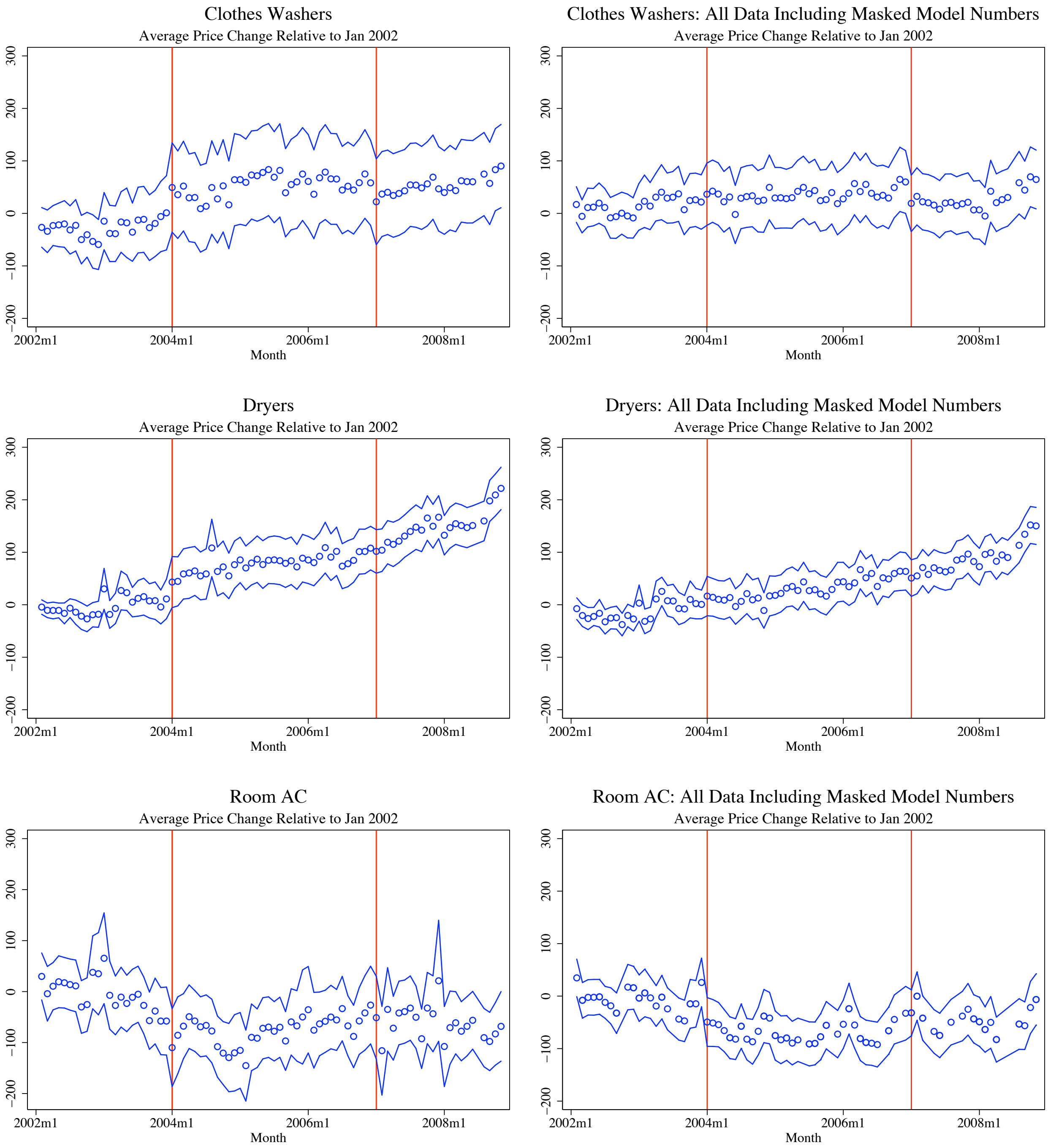


Note: Frequency of models entering and exiting the data within each efficiency category. The occurrences of the combined change in minimum and Energy Star standards are indicated by the vertical lines. The upward-facing histogram indicates frequency of new models entering the data, while the downward-facing histogram indicates frequency of models exiting the data. The efficiency categorization was only done for the year just preceding and the year just following the occurrence of each standard.

Appendix B.6: Robustness Check Including Otherwise Omitted Data

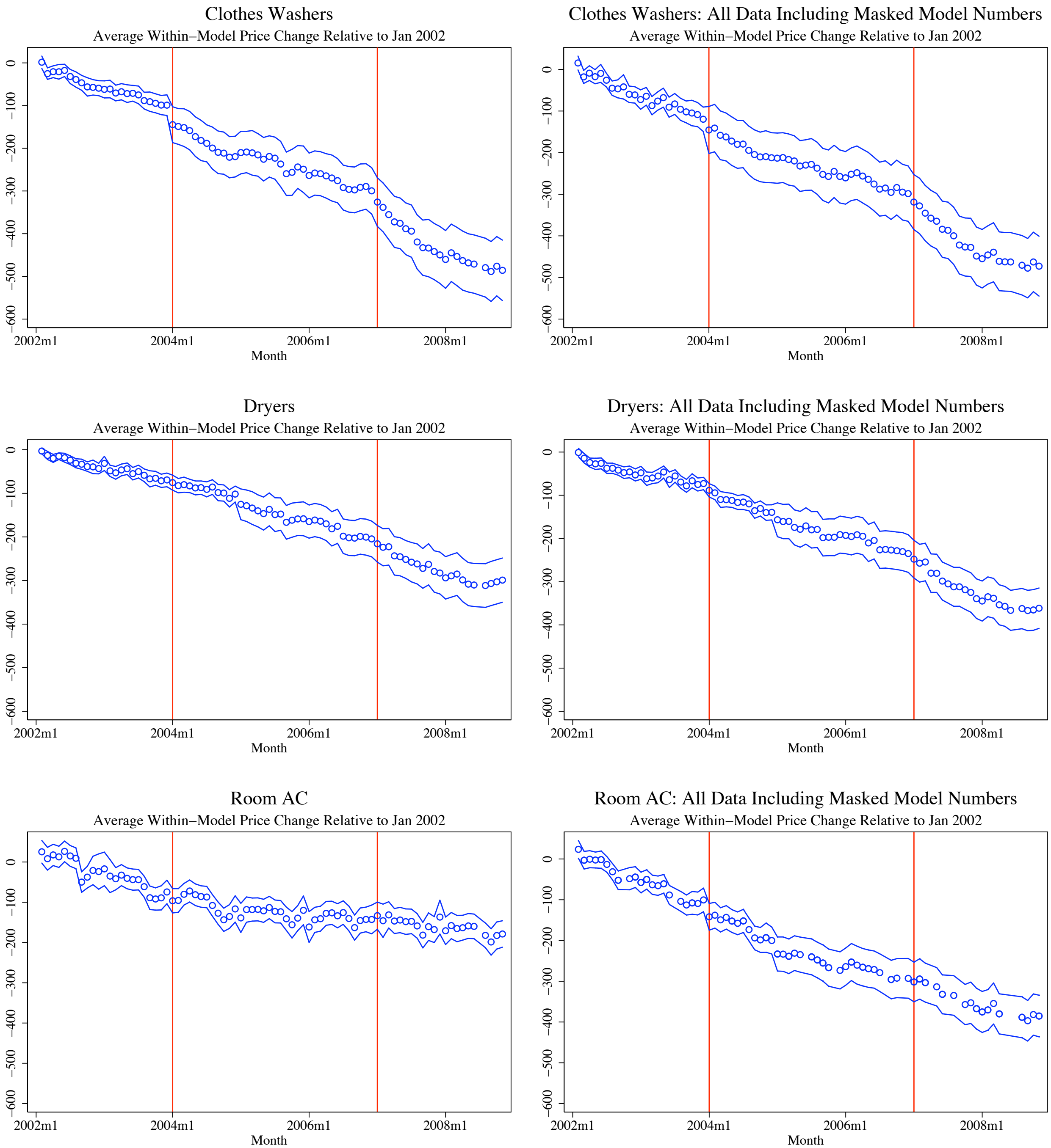
Because of the presence of masked model numbers, not all the data could be matched to the FTC kWh/year energy usage data. For this reason I chose to omit data that could not be matched to the FTC data throughout the primary analysis. However, there is concern that the omitted data is systematically different from the included data. The model numbers are masked because they would otherwise identify the retailer. A good example of products included in this category would be Kenmore products. The Kenmore brand is the Sears brand of products, and so products identifiable as Kenmore by their model number would therefore be identifiable as having been sold at Sears. Generally, Kenmore products are manufactured by the same set of manufacturers as products sold under other brands, and often are similar. For this reason, I am not overly concerned about the omitted data. However, to address potential bias introduced by omitting the masked model number data, I have done a series of robustness checks that I will present here. Namely, I have recreated the price trend figures, and the overall average regressions (not differentiated by energy usage level) with all the data. The price trend figures, comparing the original figures used in the body of the paper, and the figures with all data included, are presented in Figures B.3 and B.4. The regression results comparing the original results presented in the body of the paper, with the results when the regressions are run with all data included (not dropping the otherwise omitted observations) can be seen in Tables B.1 and B.2. Note that the regressions here which include fixed effects have to be interpreted cautiously. This is because many of the masked model numbers are aggregated together, therefore controlling for model-specific fixed effects does not actually control for individual models for some of these masked model numbers, but rather groups of models.

Figure B.3: Market Average Price Trends with Omitted Data



Note: Market-average price trends for clothes washers (top row), dryers (middle row) and room ACs (bottom row) between 2002 and 2008. The left column shows the trends for the data used in the primary analysis and the right column shows the trends when all data is retained, including observations omitted from primary analysis. All prices are real (deflated using the CPI with December 2009 base-period), and are shown relative to the average price level in January 2002. The solid vertical lines show when the standard changed for clothes washers (January 2004 and January 2007).

Figure B.4: Within-Model Price Trends with Omitted Data



Note: Market-average within-model price trends for clothes washers (top row), dryers (middle row) and room ACs (bottom row) between 2002 and 2008. The left column shows the trends for the data used in the primary analysis and the right column shows the trends when all data is retained, including observations omitted from primary analysis. All prices are real (deflated using the CPI with December 2009 base-period), and are shown relative to the average price level in January 2002. The solid vertical lines show when the standard changed for clothes washers (January 2004 and January 2007).

Table B.1: Average Price Effect at New Standard Effective Dates with Omitted Data

	2004 Standard Change						2007 Standard Change					
	No Controls		Dryers as Controls		Room AC as Controls		No Controls		Dryers as Controls		Room AC as Controls	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Var: Price	Original	Including Dropped Data	Original	Including Dropped Data	Original	Including Dropped Data	Original	Including Dropped Data	Original	Including Dropped Data	Original	Including Dropped Data
T			146.7***	167.7***	185.8***	200.9***			161.9***	131.2***	345.9***	291.3***
			(34.94)	(24.44)	(36.50)	(24.70)			(35.93)	(23.24)	(35.96)	(22.17)
Trend			-0.418	1.145	-6.444***	-2.994**			1.219	1.756	0.434	-0.161
			(1.506)	(1.198)	(2.135)	(1.316)			(1.376)	(1.104)	(2.171)	(1.105)
Standard			43.47**	5.739	18.30	-21.42**			1.271	-10.36	-8.558	-0.498
			(18.11)	(12.73)	(18.15)	(10.76)			(10.46)	(9.378)	(22.03)	(11.47)
Trend * Standard			2.877	-1.683	0.295	-0.761			4.621**	1.564	1.850	3.083*
			(2.447)	(1.860)	(2.983)	(1.670)			(2.176)	(1.662)	(3.586)	(1.679)
T * Trend	2.043	0.214	2.461	-0.931	8.487**	3.208	0.103	1.466	-1.116	-0.290	-0.331	1.627
	(2.548)	(1.995)	(2.959)	(2.327)	(3.323)	(2.389)	(2.027)	(1.670)	(2.449)	(2.002)	(2.970)	(2.002)
T * Standard	40.83	3.747	-2.635	-1.992	22.54	25.17	-29.49*	-29.93*	-30.76	-19.57	-20.93	-29.44
	(35.64)	(26.28)	(39.96)	(29.20)	(39.98)	(28.39)	(16.66)	(15.45)	(19.66)	(18.07)	(27.62)	(19.24)
T * Trend * Standard	-1.872	-0.221	-4.749	1.462	-2.167	0.540	2.651	-2.398	-1.970	-3.962	0.801	-5.481*
	(4.010)	(3.009)	(4.696)	(3.537)	(4.997)	(3.441)	(2.885)	(2.246)	(3.612)	(2.794)	(4.602)	(2.804)
Constant	614.2***	610.4***	467.5***	442.7***	428.4***	409.5***	703.3***	622.6***	541.4***	491.4***	357.4***	331.4***
	(31.96)	(22.16)	(14.15)	(10.30)	(17.65)	(10.90)	(31.41)	(20.08)	(17.48)	(11.71)	(17.52)	(9.388)
Model Fixed Effects	N	N	N	N	N	N	N	N	N	N	N	N
Observations	3,637	6,562	7,283	13,674	6,422	15,563	4,793	9,075	10,655	20,490	7,129	17,477
R-squared	0.005	0.000	0.068	0.060	0.165	0.144	0.001	0.001	0.044	0.028	0.198	0.174

Standard errors in parentheses clustered by model number

*** p<0.01, ** p<0.05, * p<0.1

Note: Results for regressions estimating the concurrent effect of the new standard (either 2004 or 2007) on the market average price of clothes washers. Columns (1), (3), (5), (7), (9) and (11) reproduce the results from the original regressions reported in Table 2.5. Columns (2), (4), (6), (8), (10) and (12) show the results of these regressions when non of the data omitted in the primary analysis is dropped. No fixed effects or controls are included.

Table B.2: Within-Model Price Effect at New Standard Effective Dates with Omitted Data

	2004 Standard Change						2007 Standard Change					
	No Controls		Dryers as Controls		Room AC as Controls		No Controls		Dryers as Controls		Room AC as Controls	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Var: Price	Original	Including Dropped Data	Original	Including Dropped Data	Original	Including Dropped Data	Original	Including Dropped Data	Original	Including Dropped Data	Original	Including Dropped Data
Trend			-3.600***	-2.411***	-7.083***	-6.956***			-5.159***	-5.218***	-2.328***	-3.585***
			(0.548)	(0.538)	(0.905)	(0.733)			(0.648)	(0.486)	(0.795)	(0.515)
Standard			-1.683	-17.20***	36.10***	7.987			-2.954	-1.838	14.50*	7.675
			(4.290)	(5.001)	(7.230)	(5.841)			(4.202)	(3.837)	(7.629)	(5.116)
Trend * Standard			0.413	-2.384***	0.762	0.317			-2.438**	-4.408***	-0.744	0.586
			(0.974)	(0.855)	(1.171)	(0.933)			(0.984)	(0.833)	(1.306)	(0.851)
T * Trend	-4.342***	-4.181***	-0.743	-1.771*	2.741**	2.775**	-5.754***	-6.282***	-0.595	-1.063	-3.426***	-2.697***
	(0.815)	(0.924)	(0.976)	(1.059)	(1.220)	(1.175)	(0.835)	(0.759)	(1.056)	(0.900)	(1.158)	(0.920)
T * Standard	-36.58***	-23.75*	-34.90***	-6.548	-72.68***	-31.74**	-13.23**	-4.361	-10.28	-2.523	-27.73***	-12.04
	(11.16)	(12.77)	(11.87)	(13.56)	(13.34)	(13.97)	(6.383)	(7.042)	(7.639)	(8.007)	(9.981)	(8.736)
T * Trend * Standard	-3.054***	-3.235**	-3.468**	-0.851	-3.816**	-3.552**	-7.079***	-6.501***	-4.641***	-2.093	-6.335***	-7.088***
	(1.098)	(1.348)	(1.461)	(1.582)	(1.609)	(1.633)	(1.371)	(1.219)	(1.687)	(1.474)	(1.901)	(1.492)
Constant	739.1***	689.7***	634.3***	589.5***	603.6***	543.6***	799.2***	718.1***	714.6***	646.2***	663.0***	551.3***
	(11.36)	(11.39)	(5.985)	(5.744)	(6.907)	(5.511)	(9.330)	(7.732)	(5.389)	(4.187)	(6.549)	(4.386)
Model Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,637	6,562	7,283	13,674	6,422	15,563	4,793	9,075	10,655	20,490	7,129	17,477
R-squared	0.235	0.084	0.209	0.104	0.223	0.126	0.319	0.203	0.300	0.218	0.293	0.165
Number of Models	418	1,049	736	1,895	790	2,331	431	1,117	959	2,459	751	2,326

Standard errors in parentheses clustered by model number

*** p<0.01, ** p<0.05, * p<0.1

Note: Results for regressions estimating the concurrent effect of the new standard (either 2004 or 2007) on the market average within-model price of clothes washers. Columns (1), (3), (5), (7), (9) and (11) reproduce the results from the original regressions reported in Table 2.6. Columns (2), (4), (6), (8), (10) and (12) show the results of these regressions when non of the data omitted in the primary analysis is dropped. Model specific fixed effects are included in all specifications. Regressions with fixed effects should be interpreted with caution, as some of the masked model numbers included here are aggregates of multiple models, and so fixed effects are not actually controling for all relevant time invariant characteristics in these regressions.