Taking LEDs to Market: Designing a Comprehensive Market Trial that Examines Incentive Levels and Consumer Preference

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ABSTRACT

This paper reports on a study by Opinion Dynamics of ambient LED lighting projects for Southern California Edison. It is based on a market pricing trial (MPT) with a quasi-experimental design, including three major big-box retailers, and a latent class discrete choice (LCDC) study as well as some qualitative components. Multiple models, retail chains, and income levels of store catchment areas were included in the MPT, and many product attributes were addressed in the LCDC study, as well as both experienced and inexperienced consumers in using ambient lighting LEDs. We found strong price effects, strong retailer effects, and income effects in the MPT. Consumers are interested in LEDs but are affected by negative experiences of CFLs. They are most interested in Reflectors, and are more willing to pay a higher price for those than A-Lines, which will need to be priced comparably to CFLs to gain customer acceptance. Several customer segments were identified for both types of lamps that can help guide targeting and messaging for future programs.

Introduction

This paper outlines the results of an A-Line and Reflector LED study focused on new strategies for the residential ambient lighting market. It summarizes the results of a comprehensive research trial that examined the following: (1) customer receptivity to LEDs, (2) price elasticities, (3) the effects of location and retailer LED sales in-store, and (4) which attributes of the lamp itself drive sales. In addition, we developed customer segments by lighting purchase preferences. See Table 1 for an overview of the study components.

Table 1. Study Components

Method	Sample Size	Date	Objectives
LED Market Pricing Trial (Pricing Trial)	Select Big Box Stores	10/2011-7/2012	• Assign varying incentive levels for LED lamps at big box stores across SCE's territory • Examine sales rates and elasticities associated with varying incentive levels • Identify correlates with sales, including location, store, and socio-economic status of the region.
Focus Groups	2 Groups	10/2011	• Examine customer lighting preferences and purchase priorities overall, specific to energy efficient lighting • Examine customer response to LED lighting demonstration • Test the LCDC instrument

Method	Sample Size	Date	Objectives
In-Home Customer Lamp Trial (Lamp Trial)	98	5/2012 to 8/2012	• Deliver 4 LED A-Lines and 3 Reflectors to 98 SCE customers • Collect data on customer installation and replacement behaviors with new LEDs • Survey "experienced" customers for the LCDC • Conduct in-depth interviews with customers who installed lamps
In-Depth Interviews (IDIs)	20	8/2012	• 20 in-depth interviews were conducted with in-home customer Lamp Trial participants • Collect customer responses to LED technology and pros and cons related to the LED's attributes
Latent Class Discrete Choice Analysis (LCDC)	252 A-Line, 224 Reflector	10/2011 and 7/2012	• Identify customer purchase priorities by LED product attribute • Classify customers into segments based on their purchase considerations • Develop market adoption models

In this paper we focus primarily on the MPT and the LCDC experiment, although some findings come from more than one study component, including in-depth interviews and focus groups. The MPT employed a real-world sales quasi-experimental design, based on three major retailer chains, covering many models of both A-Line and Reflector lamp types, with a variety of incentive levels that allowed the lamps to be offered at different prices. The LCDC experiment included customers who had experienced LED lamps (based on their participation in the in-home lamp trial) and others who had no experience of them.

Methods-MPT

The market pricing trial was conducted using an incentive field test that used quasi-experimental design techniques to obtain insight into optimal incentive levels for LED market interventions through upstream buy-downs. The field test was designed in collaboration with SCE and the trial was conducted with their channel and manufacturer partners. The study was set up with a focus on big box retailers across SCE's territory selling a wide variety of LED makes and models in the A-Line and Reflector categories. All makes and models were categorized into either A-Lines or Reflectors.

Incentive levels were assigned in geographic clusters (which we describe in the next section) to ensure that each incentive level varied by the following criteria: (1) Socio-economic status of a region, (2) Location (central vs. remote), and (3) Retailer. The field-test design was developed and modified throughout the course of the test due to varying levels of engagement and compliance among retailers. Weekly sales were then collected to examine price effects, or elasticities, based on sales volume and incentive levels.

Sample Design-MPT

Because we considered it likely that certain neighborhood and retailer characteristics would have an impact on sales in stores located within them, we employed a stratified design based on income (represented as high, medium and low tertiles) of store catchment areas (defined as 5 mile radius around the store), and whether the location[1] of the store was central or remote. We first identified naturally-occurring geographic clusters with a mix of income levels. Then we assigned incentive levels to each cluster. Our goals in assigning incentive levels were to meet the following requirements: (1) Each

[1] It turned out that this factor was not predictive, so we do not present more about it here.

incentive level should contain a similar number of stores, and an adequate mix of stores from all three participating large chains. We anticipated some differences in product display and positioning in different store chains, as well as potential differences in consumer preferences and purchase behavior. Therefore, it was important that each incentive level contain stores representing each retail chain. (2) In aggregate, the distribution of income levels (a) in the overall sample, and (b) at each incentive level should match the income distribution around all participating stores in SCE territory. Consumer purchase decisions and price sensitivity are generally related to income. Therefore, it was important that we observe sales at each incentive level from customers with a wide range of income levels. (3) Incentive levels should be assigned to minimize big differences in incentives between neighboring clusters, so that customers are less likely to comparison-shop between neighboring stores. For analysis purposes, it was important that the sales rates we would see at the end of the study reflected store-level conditions as accurately as possible, including income in the store's catchment area, and the effect of the store chain. In practice, this meant providing some separation between \$0 incentive areas and \$25 incentive areas, such as geographic distance or "buffer" stores where advanced LED products may not be available at a discount or may not be stocked.

After developing these guidelines, we tested multiple incentive level assignment scenarios and determined how well each scenario met each guideline. As would be expected in a real-world trial, the plan for distributing stores was not entirely under our control since retailers would not always agree with the plans. In the end, 117 retail stores participated in the pricing trial, each belonging to one of three major chains in SCE territory. Two additional retailers dropped out of the program or never completed agreements.

Characteristics of the Final Sample- MPT

The distribution of final sample stores by Retailer within the SCE territory was quite close to the territory-wide figures, as shown in Table 2.

Table 2. Percent of Participating Stores by Retailer: by SCE Territory and Sample

Retailers	Territory	Sample
Retailer 1	22%	23%
Retailer 2	48%	44%
Retailer 3	30%	32%

Table 3 shows the distribution of stores falling in each income level for the SCE territory and the sample, which included roughly half the stores in each chain. The distributions of sample and territory are close enough that we did not consider it necessary to weight the data by these strata.

Table 3. Percent of Stores by Catchment Area Income Level

Income Level	Territory[2]	Sample
Low	16%	19%
Medium	58%	55%
High	26%	26%

Table 4 shows that while not a balanced design, there is representation of incentive levels across income strata, as evidenced by the absence of a zero value in any cell. There were at least 2 or 3 lamp-type-store

[2] This is the distribution of income levels that have at least one of the study's participating stores within 5 miles. Income tertiles were defined by the census block groups within SCE territory. Then, the percentage of homes at each income level that have a participating store within five miles was determined to establish the income distribution of the relevant population. E.g. 16% of homes that have a store within 5 miles are in the lowest tertile income level in the SCE territory.

combinations in each income-incentive combination.

Table 4. Number of Store-Model Combinations Assigned to Incentive Levels by Income and Lamp Type

Lamp Type	Incentive Level	Income Level			Total
		Low	Medium	High	
A-Line	0	6	12	7	25
	5	3	12	3	18
	10	6	18	10	34
	15	3	7	5	15
	Total	18	49	25	92
Reflector	0	7	17	8	32
	5	5	11	4	20
	10	2	9	8	19
	15	3	10	5	18
	20	5	9	4	18
	25	2	8	3	13
	Total	24	64	32	120
Total	0	13	29	15	57
	5	8	23	7	38
	10	8	27	18	53
	15	6	17	10	33
	20	5	9	4	18
	25	2	8	3	13
	Total	42	113	57	212

Table 5 reveals how successful we were in the effort to ensure representation of all incentive levels across Retailers. There are a few cells with no lamp-type-store combinations in them, but most cells have coverage.

Table 5. Number of Participating Stores by Catchment Area Location and Incentive Level

Lamp Type	Incentive Level	Retailer			Total
		Retailer 1	Retailer 2	Retailer 3	
A-Line	0	4	21	0	25
	5	6	7	5	18
	10	10	24	0	34
	15	7	0	8	15
	Total	27	52	13	92
Reflector	0	4	21	7	32
	5	6	7	7	20
	10	5	8	6	19
	15	3	7	8	18
	20	2	9	7	18
	25	7	0	6	13

Lamp Type	Incentive Level	Retailer			Total
		Retailer 1	Retailer 2	Retailer 3	
	Total	27	52	41	120
Total	0	8	42	7	57
	5	12	14	12	38
	10	15	32	6	53
	15	10	7	16	33
	20	2	9	7	18
	25	7	0	6	13
	Total	54	104	54	212

While the design cannot be said to be entirely balanced these tables do show that there is a considerable spread of stores across conditions and characteristics so that most situations likely to affect sales are represented.

Modeling- MPT

The unit of analysis for our modeling efforts was the model-store combination. In other words, each store would appear in multiple "lines" of data, one for each model of lamp (though all lamps fell into either the general categories of A-Line or Reflector lamp types). The left-hand variable for the analysis was mean weekly sales during the study period, which lasted for about three months.

One problem that we faced was the absence of adequate sales data to represent the usual sales level for LED lighting. This was due to the absence of pre-study period sales for new products, and to comparison stores stocking, but not to being able to sell any non-price-reduced products. If this information had been available, it would have been entered as a covariate to control for general or specific sales volumes. In the absence of this type of information the team made two decisions to compensate for this problem. We used fixed-effects models with both price and mean weekly sales represented in a logged form.

A fixed effects model creates separate but parallel regression lines for each store, so that each store has its own intercept and all stores have the same mean regression line or slope. Because we used the log of average weekly sales as the dependent variable and regressed it on (log of) program retail price, the slope is equal to the elasticity, which is constant over all price levels. By not forcing every store onto the same regression line with the same intercept, the fixed effects model uses the information from each data point to calculate the best possible overall slope; in this case, the price elasticity of LED lamps in Southern California. The log-log approach also has the advantage that a store with very large overall sales will not dominate the model since each store will contribute with equal weight to the overall slope.

We wanted to combine the two product types into one model to provide more statistical power than would be possible by estimating separate models by lamp type. However, we knew from other components of this study that the consumer sees and responds to A-Line and Reflector lamps in different ways. In addition, preliminary testing showed that price had a different effect for Reflectors compared to A-Lines. We therefore included an interaction term for Reflector by price in addition to the main effect term for Reflectors. Our result is a fixed effects model that predicts LED lamp sales by price, or elasticities, for both A-Line and Reflector lamps.

Because we used log of average weekly sales, we had to designate a value other than zero for the store-model units with zero sales during the program period (because log(0) is undefined). We assigned a value of 0.04 to the store-model units with zero sales. We selected this value after several trial models and after concluding that a 0.04 substitution for zero values created the best representation of what was happening in the data. The lowest average weekly sales value was 0.05, so using a value of 0.04 allows us to include all of the zero sales units, but without allowing the zero sales data to dominate the model. Assigning zeros a smaller value, like 0.001, produced excessively high elasticities. The value set at 0.04 reduces the leverage of the large number of 0 sales data on the model calculations. The final dataset consisted of 684 store-model units.

Beyond looking at price elasticity, we modeled non-price effects. For estimating non-price effects such as retailer, income level, and location, we used a mixed-effects model. Mixed effects, or panel data models, are a hybrid of random effects and fixed effects models. The model fixes the intercept on one variable, but also accounts for the effects of other independent variables, even if the independent variables are at the store address level. Our mixed effects model calculates a unique intercept for each store address, assuming normal distribution of the intercepts.

Methods-LCDC

The evaluation team conducted an LCDC experiment with the objectives of first, understanding which attributes of LED lamps are most important to consumers; and second, segmenting SCE's customers based on their preferences as well as demographics. Our LCDC study involved two hypothetical shopping exercises completed by customers of varying experience with LEDs.

The LCDC approach generates purchaser groups by identifying product attribute preferences through a trade-off analysis. Each of the two surveys (described below) consisted of hypothetical store visits where customers selected their ideal lighting products for purchase based on the attributes of products appearing on virtual shelves. Attributes included technology type (LED, CFL, etc.), brightness, color, price, and brand. Virtual products and their attributes were presented using familiar Lighting Facts labels to simulate buyers' experiences as closely as possible.

Customers went through mock store visits eight times for A-Lines and eight times for Reflectors. For each visit, customers selected the product they were most likely to buy as well as products they were least likely to buy based on the product attributes. They could also choose not to buy at all. In this way, the exercise mimics actual shopping experiences.

Attributes were assigned to virtual products offered in each hypothetical store according to a formal experimental design. In building the design, we adhered to two principal objectives. First, we wanted the product attributes to be completely uncorrelated with each other; second, we wanted each level for every attribute to appear an equal number of times throughout the entire design. The statistical terms for these desirable characteristics are orthogonality and balance, respectively. The better the orthogonality and balance, the more efficient the design.

Fortunately, the research community has assembled an extensive library of arrays that meet these criteria. A particular class of arrays having perfect orthogonality and balance is available, two of which were used to develop the experimental designs for this study. Table 6 shows the attributes and their levels that appeared on products participants were exposed to in the survey.

Table 6. Variables Available for Latent-Class Discrete Choice Models

Attribute	Level	A-Line	Reflector
None of these	Prefer not to buy	√	√
Bulb type	LED - A-Line [appears twice[3]]	√	
	CFL	√	
	Halogen	√	√
	LED - PAR Reflector		√
	CFL Recess		√
	LED - Recessed Trim		√
Brand	Familiar brand	√	√

[3] We deliberately unbalanced the design to ensure we had an adequate number of choices for LED's, the focus of our study.

Attribute	Level	A-Line	Reflector
	Unfamiliar brand	√	√
Outlet	Lighting store	√	√
	Drug store	√	√
	Hardware store	√	√
	Online lighting-only store	√	√
	Big-box mass retailer	√	√
	Grocery store	√	√
	Big-box building supplies retailer	√	√
	Online retail store	√	√
Price	$1	√	
	$5	√	√
	$10	√	
	$15	√	
	$20	√	
	$25		√
	$30	√	
	$40		√
	$50	√	√
	$65		√
	$75	√	√
	$100		√
Brightness, wattage equiv.	40 Watt	√	√
	60 Watt	√	√
	75 Watt	√	√
	90 Watt		√
	100 Watt	√	
Color temp.	2700K (warm white)	√	√
	4100k (cool white)	√	√
Energy Star	Energy Star	√	√
Beam angle	180 degrees	√	
	270 degrees	√	
	Flood		√
	Spot		√
Glare	Glare		√
Dimmable	Dimmable	√	√
Life (yrs)	2 years	√	√
	8 years	√	√
	20 years	√	√
	30 years	√	√

Surveys-LCDC

Overall, 252 customers completed the LCDC surveys (see Table 7), but 28 customers did not complete the Reflector proportion of the shopping experience (bringing the sample size for Reflectors to 224). Two samples were used in the analysis meant to represent both the general population and "experienced" customers.

Table 7. LCDC Survey Sample Sizes

Survey	A-Line Respondents	Reflector Respondents
General Population Survey	181	155
"Experienced" Customers Survey	71	69
Total	**252**	**224**

A total of 181 customers completed the general population survey, which consisted of customers who had little to no experience with LEDs. The results of this survey represent the lighting product market in its current state, before mass-scale awareness of LEDs.

Ninety-seven "experienced" customers participated in the Lamp Trial. Of these, 71 completed an online survey that included the shopping exercise (2 did not complete the Reflector portion). Because these customers had the opportunity to experiment with LEDs in their home for an average of eight weeks before completing this survey, the results from this "experienced" customer survey may provide a view into the residential lighting market once LEDs have fully entered it and most consumers are aware of or have experienced LEDs.

Results-MPT

Figure 1 shows the relationship between price and sales (both in logged form) by retailer for both A-Lines and Reflectors. The x-axis in each chart is the log of price (getting smaller as you move from left to right), and the y-axis is the log of average weekly sales. Each dot on the graph represents one unique store/model combination. The lines that are drawn through the chart are the best-fit regression lines that show how sales tend to go up as price goes down for each retailer. The A-Line chart reveals a clear upward trend for sales as price goes down. However, the Reflector chart reveals a much steeper incline for sales as price goes down. This indicates a strong price effect for both, but especially for Reflectors. In addition the colors of the dots represent the three retailers in the study. It also reveals the differences in the price effects by retailer chain. The price effects are noticeably stronger for Retailers 2 and 3. It is also possible to see a generally higher overall sales rate in Retailer 1.

Figure 1. Log of Average Weekly Sales vs. Log of Program Retail Price and Retailer

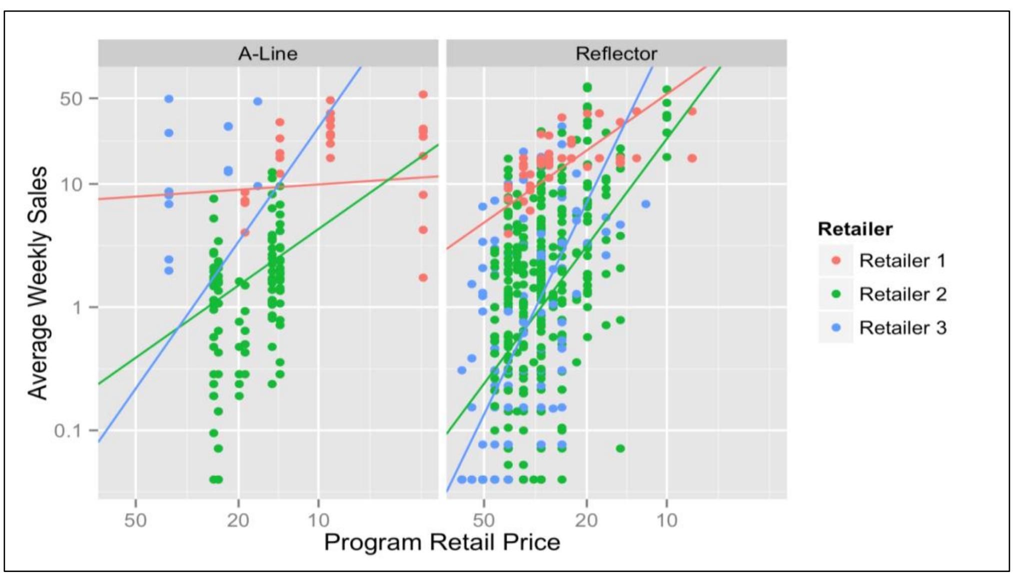

Table 8 shows the results of the fixed-effects model predicting (log) mean weekly sales that includes the predictors of (log) program price, dummies for A-Lines and Reflectors, and the interaction between (log) program price by Reflector. The price elasticity for A-Lines is 1.14, and for Reflectors is 3.25. In other words, as price goes down by 1%, sales of A-Lines go up by 1.14%, and as price for Reflectors goes down by 1%, sales go up by 3.24%. These reveal strong price effects for both products, but especially for Reflectors. In both cases, prices are elastic, indicating that a percentage change in price results in a greater percentage change in demand.

Table 8. Fixed-Effects Model Estimating Price Elasticities

Variable	Coefficient	Std Err	t-Value
log(Program Retail Price)	-1.13501	0.34219	-3.317
A-Line Dummy	2.45094	1.14836	2.134
Reflector Dummy	9.85416	1.13638	8.672
log(Program Retail Price) X Reflector	-2.11912	0.30903	-6.857
Note: Adjusted R-squared=.5458, F=7.85, df=120, 564, p < 0.0001			

Table 9 shows the results of a mixed-effects model (without store-specific intercepts) that contains both price and non-price predictors. This model was estimated in order to be able to study the non-price effects on sales. Therefore, the price effects shown in this table are not interpreted since they were better estimated and interpreted by the fixed-effects models. The coefficients in Table reveal a very strong retailer effect. Interpreting the coefficients, all other things being equal, Retailer 3 would be expected to sell about 7.7 times as many lamps as Retailer 1.

Income shows a smaller, though statistically significant effect. The model also confirms what we saw in other parts of this study, namely that Reflectors appear to be a more popular product compared to A-Lines. Reflectors sold at almost 5 times the rate of A-Lines. Whether the store is located in a central or a remote location is not a significant factor in sales. These findings represent a test of the early introductory market phase of these products, which could last a few years. Based on historic incandescent and CFL market share tracking, the popularity of LED Reflectors over A-Lines is not expected to continue over the long term.

Table 9. Model of Price and Non-Price Factors Predicting Log of Average Weekly Sales

Variable	Coefficient	Std Err	t-Value
Intercept	1.81719	0.81293	2.235
log(Program Retail Price)	-0.14274	0.2924	-0.488
Retailer 2	2.29275	1.15693	1.982
Retailer 3	7.74467	1.77059	4.374
Reflector	4.80266	1.07345	4.474
Income Level 2	0.80334	0.19282	4.166
Income Level 3	1.41888	0.22371	6.342
Remote Location	-0.09298	0.14843	-0.626
log(Program Retail Price) X Retailer 2	-1.35905	0.37174	-3.656
log(Program Retail Price) X Retailer 3	-2.90437	0.52323	-5.551
log(Program Retail Price) X Reflector	-1.35583	0.35724	-3.795

Results-LCDC

Customers treat A-Lines and Reflectors in different ways. Our work has shown (from multiple study components) that customers have very distinct purchase and shopping preferences for A-Lines vs. Reflectors, indicating these categories are decidedly different purchases for consumers and show no evidence of cross-elasticity of demand. After price, customers select products for purchase based on different attributes depending on whether they are selecting A-Lines or Reflectors. Specifically, energy savings, product type (CFL vs. LEDs), and long-term savings drove A-Line selection. For Reflectors, product type, the purchase location or outlet, and brightness drove product selection.

Customers are more receptive to LED technologies for Reflector purchases. Our data suggest that customers are more interested in LEDs for Reflector technology. This is backed up by our Lamp Trial (not reported here) as well as our LCDC results.

The LCDC survey also used purchase preferences for A-Lines and Reflectors to develop shopper groups for each of the two product categories. Shopper groups are sets of customers who share common preferences for bulbs and whose preferences differ sharply from those of other groups. Here we briefly describe the shopper groups that emerged from this study.

Customer Purchase Groups

Tables 10 and 11 present descriptions of each A-Line and Reflector shopper group, giving a brief overview of relative potential sales (based on the percentage that preferred LEDS), and each group's needs.

Table 10. A-Line Purchaser Group Snapshot

LED Rating	A-Line Segment	Needs. . .
★★★★ % Preferred LEDs: 84%	Tech Seekers (25%)	➢ The latest technology ➢ To feel confident they are getting the cutting-edge ➢ An opportunity to explore
★★★ % Preferred LEDs: 15%	Practical Shoppers (30%)	➢ Clear information ➢ Reasonable price ➢ Believable longevity claims
★★ % Preferred LEDs: 16%	Convenience-Focused (14%)	➢ Easy purchase decisions at places they already shop
★ % Preferred LEDs: 2%	Thrifty DIY-ers (31%)	➢ A clear understanding of how LEDs save money and improve the home ➢ Reasonable price

★ Opportunity Rank for Marketing LEDs

Table 11. Reflector Purchaser Group Snapshot

LED Rating	Reflector Segment	Needs. . .
★★★★ % Preferred LEDs: 48%	Product Explorers (24%)	➢ Demonstrations ➢ Accessible, online information ➢ Trusted reviews
★★★ % Preferred LEDs: 82%	Energy Investors[4] (49%)	➢ Efficiency without a cost premium, will not likely consider LEDs until prices drop dramatically ➢ Clear information on energy and lifetime cost savings
★★ % Preferred LEDs: 21%	Value-Focused (14%)	➢ Bang for their buck ➢ At the shelf information promoting product savings
★ % Preferred LEDs: 59%	Deal-Sleuths (13%)	➢ To feel like they're getting a "steal" ➢ To save the most they can with every purchase

★ Opportunity Rank for Marketing LEDs

While the A-Line and Reflector group sets share some similarities, they do not overlap in a systematic way. For instance, both sets have an early adopter group (Tech Seekers and Product Explorers), but customers in the A-Line early adopter group do not typically appear in the Reflector early adopter group, indicating that different customers will take different risks at the shelf depending on the product they are considering. Furthermore, both sets of shoppers have a value-driven group (Thrifty DIY-ers and Value-Focused Browsers). However, only 12% of value-driven A-Line shoppers are value-driven Reflector shoppers.

Summary

The LED market is very price sensitive. While no ideal "sweet spot" was identified for specific incentive levels or prices to increase sales, several discoveries emerged from the Pricing Trial that could help optimize incentives in programs. Reflectors and A-Lines showed different reactions to price reduction. Reflectors gained the greatest return on sales, selling at almost five times the rate of A-Lines. For every 1% decrease in price, there is a 1.14% increase in A-Line sales as compared to Reflectors, where a 1% decrease in price means 3.25% increase in sales. LEDs sold much better when their prices were relatively close to the price of an equivalent CFL of the same type. Products with prices $20 or less sold the best in all categories. High prices are unacceptable to customers: Irrespective of product type, income level, or other test factors, sales at prices above $40 were virtually non-existent.

High-income areas had the greatest sales rates when controlling for other factors. On average, LED lamp sales in high-income areas were 4.1 times higher than sales in low-income areas and 1.9 times higher than stores in medium-income areas. LED lamp sales in medium-income areas were 2.2 times higher than in low-income areas. We note here that this may not appear to be the case when examining the raw data; however, factors that covary with medium-income store locations (such as retailer chain) drive up middle income sales. When controlling for these factors, we see that high-income areas have the greatest sales volume.

There is significant variation in sales by retailer. Our data suggest that some retailers outperform others exclusive of the independent variables we tested. Although most programs are aware of the retailers that consistently sell at higher or lower volumes, this test verifies that the choice of retailer is important because some sell LED products significantly faster and in higher quantities than others.

[4] We note that this group was placed lower on the opportunity hierarchy because of their extreme price sensitivity despite high interest in LEDs.

Region had no statistically significant effect on sales. Our data show that centrality to the L.A. Basin had no statistically significant effect on sales.

As found in our Pricing Trial, our LCDC work confirmed that customers are extremely price sensitive and that price is the number one purchase decision for lighting. Price was the primary driver of customer lamp selection among LCDC survey respondents indicating that price, when accounting for all other product attributes, determines which lamp customers were willing to select. This finding suggests that incentives would be an effective component of any LED support program.

As demonstrated in the Pricing Trial, our qualitative research indicated that customers will accept LED lamps priced comparably to Compact Florescent Lamps (CFLs). Notably, customers indicate they will pay a premium for LED Reflectors, even though our Pricing Trial indicates high sensitivity to price for this category. Specifically, customers indicated that they would pay as much as but no more than $10 for LED A-Lines and $30 for LED Reflectors. This indicates that customers are receptive to LED technologies for this particular category, and when considered with the Pricing Trial findings, the data suggest that marginal drops in price will net greater gains in purchases for this product due to customer interest. These data also suggest that the price floor could be higher for Reflectors relative to A-Lines. We recommend additional research and tests to further examine this phenomenon.

Customers are leery of LED technologies due to (1) little to no direct experience with the technology, and (2) negative past experiences with CFLs. Due to low levels of self-reported exposure to ambient LEDs, customers tend to expect similar drawbacks to new LED technologies that were indicative of the early rollout of CFLs. Primarily, customers are concerned about lighting quality, ability to dim smoothly, flickers, and realization of longevity claims. Other concerns include disposability and safety.5 Once experiencing LEDs, customers prefer the lighting quality of LEDs but skepticism lingers about unobservable attributes such as longevity. Customers are overwhelmingly satisfied with LED light quality and prefer it to CFLs once they have had the opportunity to directly experience the product. However, this enthusiasm about LED quality is tempered by lingering concerns that the longevity claims will not be borne out.[6]

Customers treat A-Lines and Reflectors as different products. Customers have very distinct purchase and shopping preferences for A-Lines vs. Reflectors, indicating these categories are decidedly different purchases for consumers. After price, customers select products for purchase based on different attributes depending on whether they are selecting A-Lines or Reflectors. Specifically, energy savings, product type (CFL vs. LEDs), and long-term savings drove A-Line selection. For Reflectors, product type, the purchase location or outlet, and brightness drove product selection. Customers who tried LEDs in their homes expressed clear preferences for product attributes. Specifically, customers are looking for warmer color temperatures; smooth, linear dimming; 100-watt equivalent lamps; and wider beam angles (115 degrees or more) for Reflectors.[7] Interviewed customers are more receptive to LED technologies for Reflector purchases. Our data suggest that customers are more interested in LEDs for Reflector technology. This is backed up by our Lamp Trial as well as our LCDC results.

[5] This comes from the focus groups done before quantitative data collection, but not described here due to space limitations.
[6] This comes from in-depth interviews with customers receiving program lamps through the study. The interviews are not described in this paper due to space limitations.
[7] This also comes from in-depth interviews.