Daylighting and Productivity in the Retail Sector

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ABSTRACT

In this paper, we present the methodology and findings of a replication study that found statistical evidence that increased hours of daylighting is associated with increased retail sales. The original study, conducted by Heschong Mahone Group for PG&E in 1999, found a strong, positive relationship between the presence of skylighting and increased retail sales. This new study, supported by the California Energy Commission's Public Interest Energy Research (PIER) program, was designed to determine if the findings of the original study could be replicated for a second retail chain in an entirely different retail sector, and also examine additional influences on sales not considered in the first study.

Monthly sales data for three years were analyzed for a set of seventy-three store locations in California belonging to a certain retail chain, twenty-four of which had a significant amount of daylighting. The design and operation of all stores was fairly standard, with enough variation in daylighting practices to allow for a scalar representation of the presence of daylighting.

Multivariate regression modeling techniques were used to explore the effect of daylighting on retail sales, while simultaneously controlling for the influence of approximately fifty other variables, such as store size and age, which could influence sales. These regression models found that increased hours of daylight per store were strongly associated with increased sales and increased transactions, but at a smaller magnitude than the original study.

Additional findings and limitations of the study will also be discussed, along with possible mechanisms for this effect.

Introduction

This paper describes a study that presents evidence that a major retailer is experiencing higher sales in daylit stores than in similar non-daylit stores (Heschong Mahone Group 2003). Statistical models were used to examine the relationship between average monthly sales levels and the presence of daylight in the stores, while simultaneously controlling for more traditional explanatory variables such as size and age of the store, amount of parking, local neighborhood demographics, number of competitors, and other store characteristics. The retailer, who remains anonymous, allowed us to study 73 store locations in California from 1999 to 2001. Of these, 24 stores had a significant amount of daylight illumination, provided primarily by diffusing skylights, where photocontrols turned off electric lights when sufficient daylight was detected.

The current study was performed as a follow-on to a similar study completed for Pacific Gas and Electric in 1999 (Heschong Mahone Group 1999a), which found that for a certain retail chain, all other things being equal, stores with skylights experienced 40% higher sales than those without skylights. The initial study was reviewed by a panel of experts, recruited by Lawrence Berkeley National Laboratory, involving a wide range of disciplines related to the study. In general, the review panel was satisfied with the soundness of the basic methodology and the rigor of the statistical analysis. There were, however, some weaknesses to the original study and lingering peer review questions that could only be addressed in follow-up studies (Heschong Mahone Group, 1999b), which are described below.

1. **Replicating findings:** The biggest weakness in the original study was that the participant remained anonymous, making it impossible for anyone else to verify the findings. Anonymity was difficult to overcome, since it was unlikely that any retailer would be willing to reveal their identity in a study that publicly discussed sales effects. However, a second study, of another retailer, would increase confidence that such a skylighting effect could be replicated.
2. **Controlling for other influences:** The original study controlled for twelve potential influences on sales. Not all stores in the study were visited to verify conditions. It was highly probable that there were other factors affecting sales that were collinear with skylighting that the original research team could not determine. A more detailed study, including verification visits to all sites in the study, and collection of more information about store characteristics, should be able to reduce the uncertainty that other factors collinear with skylighting might actually be responsible for the original findings.
3. **Bounding the effect:** The 40% increase in sales associated with skylighting seemed to be improbably high. At best it could be assumed to be an upper bound of an effect. If we found positive sales associated with daylighting in another chain, could we establish upper and/or lower bounds to the effect?

The study described in this paper, supported through the California Energy Commission's Public Interest Energy Research (PIER) program (Heschong Mahone Group, 2003), was designed to address these concerns, while also expanding other areas of our knowledge about the interaction of retail sales and daylighting. In this study, a second retailer was identified who had appropriate conditions for such a study, and who was willing to participate in the study. As with the original retail study, strict anonymity was requested and observed.

The Study Participant

The selected study participant, hereafter simply called “the retailer,” is a large chain retailer who initially indicated that between 50 and 100 sites could be made available for our study. At a minimum, the retail participant would be a large chain retailer with consistent characteristics across stores, have a large number of stores within a relatively small geographic area, have some daylit and some non-daylit stores, maintain a database on each store’s performance, be willing to participate, and be willing to allow the study results to be published publicly. Other desirable but not required characteristics were that the participant retailer would allow us to collect data at each store location, have little variation between daylit and non-daylit stores other than the amount of daylighting available, be in a different retail sector from the participant in the original study, allow us to interview store customers, and allow us to interview store personnel. The participant met all of our minimum selection criteria and all of our secondary ideal characteristics with two notable exceptions. As in the previous study, the participant requested anonymity. In addition, while they allowed us access to store sites and interviews with employees and managers, they requested that no customers be contacted or interviewed.

Reviewing the corporate files, we identified 73 store sites that met our study criteria, which were all located in California. Of the sites included in the study, all but two were single story buildings. 24 of the 73 sites had some form of daylighting, primarily with diffusing skylights. While there was a fairly standard store plan and skylight design, there was enough variation in how the daylighting was accomplished among the daylit stores that we were able to treat the presence of daylight as a scalar variable, rather than as a simple yes/no variable as in the previous study.

Data Collection

We collected data for the study from a number of sources. First, we collected as much data as possible from the retailer directly, using corporate records, plan rooms, and interviews with corporate managers. We then conducted on-site surveys of each store in the study to confirm information from the corporate records and to collect new, detailed data about the physical conditions at each store. Simultaneously, we collected and processed Census and market conditions information from various public databases, using GIS analysis to create site-specific information.

Physical Characteristics Data

Using telephone and in-person interviews with corporate managers, we gathered information about the history of particular stores and why some sites had skylights while others did not. This historical data helped us to determine if there were any factors that might prove collinear with skylighting and store sales performance. We learned that the retailer had a wide variety of ownership/tenant relationships for their store sites. Skylights were typically installed in sites that were acquired for construction of a new store, regardless of whether the store site was to be owned or leased. Stores without skylights typically had been acquired from another chain and remodeled to meet the retailer's needs. The company felt that it was too expensive to retrofit skylights into an existing store shell. Occasionally skylights were added to older store sites when extensive remodels were undertaken.

Based on our assessment of available data, we determined that we needed to visit all 73 study sites, to collect additional information and verify the information provided in the corporate records. The retailer gave us parameters of when and how to conduct the surveys to minimize any intrusion on store operations. We had to limit each site visit to less than one hour, and minimize the use of instrumentation. We were limited to data that we could reliably collect within the one-hour site visit. In addition to simple observation, photography and instrument readings, we were allowed to interview the store manager and ask the manager to have employees complete a simple lighting quality survey.

Site visits were scheduled during non-peak sales periods and were completed within 30 to 60 minutes. Visits to skylit stores were scheduled towards the middle of the day, between 10 AM and 3 PM, in order to measure full daylight conditions. Non-skylit stores were often visited earlier or later, or even at night, since we were only measuring electric illumination. The site visits were completed from late January to early March of 2002.

Census Demographic Data and Local Market Analysis

From our previous retail daylighting study, we learned that the ZIP-code level census data did not predict retail sales particularly well. The two census variables used in the original study, average household income and total population by zip code location of the store, only achieved 95% significance as predictors of store sales performance, and together only explained 3% of the variation in the data. Our goal in the current study was to use better demographic predictors of store sales.

We reviewed 34 possible census characteristics with the real estate manager of the retailer, and together selected twelve characteristics that represented a range of population, economic, ethnic, housing, and transportation information, and that were considered most relevant to this particular chain's target customer. A GIS consultant processed this information into ten census variables for each study site. Since each variable was based on census data within the area determined by a standard radius, the census variables also became density indicators for each site.

At the time of our data collection, the 2000 US Census data was just becoming available. Population and ethnic characteristic data was available for the 2000 census, but for housing, economic and transportation data we had to use 1990 data. The difference between the 1990 and 2000 population data determined growth rates for the sites.

We also used a GIS mapping database to locate competitors close to the subject store sites. The retailer told us whom they considered to be their major competitors. We determined the number of these competitor stores within a "standard" analysis radius and twice the standard radius of each site.

In addition, co-tenants for any site were observed during the site visit and assigned a scalar of 0-4 based on the store type, size and typical intensity of customers use. A zero indicated no co-tenants, one indicated small local stores, while a four indicated an extremely large (big-box) co-tenant with a steady stream of customers.

The retailer also told us that they had observed an effect whereby additional stores of the retailer in a given area tended to boost sales for all stores in that area. This was attributed to the advantages of co-advertising within a given media market and additional local customer awareness of the stores. To account for this effect, we create a "sister store" scalar. We mapped the retailer's stores and counted the number of stores sharing a similar media market. The store locations were rated, on a scale of 1 to 5, for the density of other sister stores nearby from the same chain. A store with a rating of 1 was alone in its media market, while a store with a rating of five had the highest density of sister stores nearby.

Data Processing and Variable Definition

Upon completion of data collection and verification, the data was processed into useful variables for analysis. Forty-one explanatory variables and two dependent variables were ultimately defined and included in the preliminary analysis. These variables took the form of binary variables (yes/no) or scalar variables (a range of values indicating relationships from small to large). In order to preserve the anonymity of the participant, not all information about the variable definitions or ranges can be revealed. For reporting purposes, most variables were transformed into a dimensionless scalar in order to mask identifying information about the retailer.

The retailer provided us with 34 months of monthly sales totals and number of transactions per store site, transformed into dimensionless scalars. The 34 month study period included the California "power crisis" of 2001, when most retailers in California agreed to operate their stores at one-half of normal electric light levels in order to reduce peak loads on the state electric grid.

During normal operations, our participant had used automatic photocontrols to reduce electric illumination when sufficient daylight was available in daylit stores, while non-daylit stores were operated at full light output at all times. During the 10-months of the power crisis, all stores were operated at reduced illumination levels. Thus, the automatic photocontrols were overridden and both daylit and non-day lit stores were at approximately one-half normal electric illumination levels at all times.

We took advantage of this change in operation to create a natural experiment. We divided our data into two periods: a 24-month period of normal lighting system operation, during 1999-2000, and a 10-month period when all stores were operated at about one-half of normal illumination, during 2001.

Daylight Variable Definition

In the previous retail study, we were only able to describe the presence of daylighting as a yes/no variable. We were assured in that study that the skylighting design was highly standardized in all stores, which seemed to be confirmed by visits to a sample of sites. Thus, a yes/no variable seemed a reasonably accurate description of conditions for these stores. However, in this newer study, we hoped to use a more sensitive metric to describe the amount of daylight in the stores. The new participant had a greater variety of daylighting conditions, including differences in the type, amount and placement of skylights, and also included a few stores daylit from roof monitors or clerestories.

We decided to use the number of daylit hours above a certain threshold illumination as the daylight metric. Threshold illumination was defined as the electric design horizontal illumination in non-daylit stores. Thus the daylight hours variable could capture the variation in both intensity and duration of daylight due to climate location, daylight system and store interior design. When only a sub-area of the sales floor had useful daylight, the daylit hours were calculated for that sub-area, then proportioned relative to the size of the store. Thus, if only one half of the sales area was daylit, the annual daylight hours were reduced by half.

Number of daylit hours per year per store was predicted by running computerized hourly simulations of each store. This was fairly easy for the standard skylit stores, using the automated spreadsheet SkyCalc®. It was more difficult for the few stores using non-standard daylighting systems, such as clerestory windows or roof monitors. For those, we used an annual DOE-2 model, which could account for the effects of vertical glazing (Heschong & McHugh, 1999; Heschong & McHugh, 2000).

Statistical Methodology

The heart of this study was the statistical analysis of the data collected. The analysis entailed developing statistical models that sought to explain the factors that affect retail sales in this particular chain. Our goal was to control for other influences on sales in order to isolate the effect of our key variable of interest: daylighting. Developing these models requires reasonable experience with what is likely to influence sales, a thorough understanding of how reliable the available data is, and a certain amount of trial-and-error looking for mathematical models which best fit the data. A variety of statistical tests were used to determine which modeling approach provided the most mathematically accurate representation of the data. All data were examined for heteroscedastic and collinear relationships.

All analysis was pursued using multivariate regression models in SAS using a variant of backwards step-wise regression to eliminate the least significant variables. F-tests were performed on groups of variables to insure that they could be dropped as a group as well as individually. The analysis used $p \leq 0.10$ as the threshold for the inclusion of explanatory variables in the models, meaning that for a variable to be considered significant in determining sales, there must be no greater than a 10% chance of error in making this decision, or 90% certainty.

We had a very long list of potential explanatory variables that we wanted to consider in this study. To simplify the process of identifying the most significant variables, we began by running simple models, first considering just the corporate level information, then adding the demographic, marketing and environmental variables in groups.

We ran a series of preliminary models testing these variables for consistency between both the 10-month and the 24-month models. We settled on a core demographic model with the highest R^2 and the most consistent set of explanatory variables.

Replication Model

Once the core demographic model was defined, we attempted to replicate the simple models that had been used in the previous Retail and Daylight study. For this model, daylight was defined as a simple yes/no variable. In the original study, we had used zip code-based census information. Here, we used the more detailed, and presumably more accurate, census information by radius. We also used information about the market conditions of each store. We did not, however, include environmental characteristics about each store.

In the replication models, the yes/no daylight variable was not significant. The R^2 of the models was higher than the previous study (R^2 went from 58% to 69%), suggesting the other variables we included were increasing our precision in predicting sales. While the new census variables were significant, they were not consistent across both models.

Creating Interaction Variables

We discovered early in our analysis that many of the variables we defined were highly correlated with each other. Some of these had a fairly obvious causal explanation, such as higher ceiling heights in the daylit stores. Others sets of correlated variables had no obvious explanation, such as the observation that daylit stores tended to have slightly larger parking lots.

In order to account for all potential correlations between daylight and other variables, we undertook two tasks. First we ran a test model with the daylight hours as the dependent variable, which highlighted those variables most strongly correlated with daylight. We were pleased to find that the explanatory variables that predicted daylight were not the same as those that predicted sales. Second, we identified a set of interaction variables for inclusion in the final models, which would account for interaction effects between the presence of daylight and other significant variables in predicting the sales index.

The use of interaction variables made for more precise models, but also made them a bit more difficult to interpret directly. Interaction variables basically describe second-order effects, which modify the primary effects of the two variables considered. With interaction variables, the effect of more daylight in the stores can only be understood relative to the other influences on the daylight effect.

It is important to recognize that the models using Daylight Hours with interaction effects are far more complex than the simple Daylight Yes/No models used in the previous study. The simple Yes/No Daylight models predicted the same daylight effect for every daylit store. The predicted daylight effect per store was calculated by applying the model's equation to each store's specific characteristics relative to its daylight hours and interaction variables.

This is a much more nuanced approach to studying the effects of daylight. Sometimes the daylight effect for an individual store is predicted to be positive and sometimes it is negative. The key issue of interest is whether the net effects of daylight across the fleet of stores in the chain is positive or negative. Using the interaction variables, we calculated the predicted sales for each store according to the models, and then summarized the net effect on the chain.

Linear Versus Log Models

The mathematics of regression models can take different forms, depending on the kind of effect one is studying. In many studies, linear regression models are perfectly adequate, and this is the type of model that was used in our previous daylighting and retail sales study. For this study, however, we tested two types of models, one using the linear sales index and the other using the natural logarithm of the sales index. Log variables have often been found to be highly appropriate for models dealing in economic functions, or variables likely to have diminishing effects as their size increases. Since our models were dealing with sales indices, and were also likely to include diminishing effects, this was deemed appropriate. For the log models, we also took the natural log of any explanatory variable where it was appropriate. Specifically, the explanatory variable had to meet the mathematical criteria of the natural log function and also had to have a logical explanation for why a diminishing effect might be expected as the scale of the variable increases. In the log models, in addition to the sales index, the following explanatory variables were also logged: Sales Area, Store Age, and Parking.

We used a number of criteria to compare the validity of the linear and log models. The primary criterion was the mathematical "fit" of the models, as expressed in the R^2. The explanatory power, as expressed in R^2, of all models is quite high. However, it is not appropriate to directly compare the R^2 of linear and log models, since the dependent variables are not defined on the same scale. An appropriate comparison between models of this type is called the "Box-Cox Transformation". Using this method, we found that there was virtually no difference in the explanatory power of the two sets of models. Thus, they were judged equally good at explaining the data.

We then applied secondary criteria to compare the models, including parsimony of the models, consistency between the two time periods, and reasonableness of the predicted effects. While both the linear and log models were comparable in terms of parsimony and consistency, the log models predicted a more moderate range of effect for the daylight variable, and thus were judged to be the more conservative and appropriate choice. Thus, in this paper we will discuss only the findings of the log models.

Analysis Findings

The log models had consistent explanatory variables for both the 10-month and the 24-month time periods, except for one additional interaction variable in the 10-month model. The magnitude of each variable's effect and significance are also quite similar. The R^2 of the log models are 74.7% and 75.7%. Thus, we are explaining about 75% of the variation in the sales data between stores, while 25% remains unexplained due to other factors not considered, or just random variation.

Figure 1 lists the variables the log model found significant in predicting the sales index, along with their magnitude and significance. The variable with by far the strongest positive effect on sales was the size of the sales area (i.e. the size, or square footage, of the store dedicated to sales). Other variables with positive effects include the age of the store, the number of sister stores nearby, and a more educated local population.

Figure 1. Results of Log Models

Model Name: LN 99, 00		
Variable	**B**	**Sig.**
logArea	7.694	0.001
logAge	0.246	0.000
Transport	-0.00002	0.000
Education	0.00001	0.001
Co-mktg	0.091	0.000
Compet 1	-0.056	0.004
Height	-0.161	0.023
logPark	-1.823	0.000
out440	0.651	0.002
DayHrs	-0.00057	0.003
ParkDH	0.00024	0.002
Model Summary:		
RMSE	0.19	
R^2	74.7%	

Model Name: LN 01		
Variable	**B**	**Sig.**
logArea	6.133	0.002
logAge	0.305	0.000
Transport	-0.000014	0.000
Education	0.000004	0.001
Co-mktg	0.072	0.000
Compet 1	-0.047	0.004
Height	-0.140	0.007
logPark	-1.828	0.027
out440	0.651	0.002
DayHrs	-0.00040	0.003
AgeDH	-0.00003	0.092
ParkDH	0.00024	0.015
Model Summary:		
RMSE	0.17	
R^2	75.7%	

In log models, a one-unit change in a non-logged explanatory variable predicts an approximate B percent change in the sales index, and for logged explanatory variables, a one-percent increase in the explanatory variable predicts an approximate B percent change in the sales index. So for example, in these log models, since square footage was also logged, as the size of the store increases by one percent, the sales index increases by approximately 6-7 percent.

While the B-coefficient for the Daylight Hours variable appears negative in these models, the actual net daylight effect turns out to be positive, once the effects of the interaction variables, Parking * Daylight Hours and Age of Store * Daylight Hours, are taken into account. To calculate the overall effect of more daylight on corporate sales, we first calculated the effect of daylight on each individual store, considering all interaction effects specific to each store. We then totaled the effects on all daylit stores, and divided by the sum of all sales for those stores, to calculate the "net daylight effect," or the average predicted effect on sales for adding daylight to any store in the chain.

The Log Models find that adding daylight to stores (based on the norm of the corporate design, or about 1090 hours of useful daylight per year, or about ¼ of the total yearly daytime hours) will be associated with a "net daylight effect" showing an increase in sales, as shown in Table 1 below:

Table 1. Net Effect of Daylight on Sales, Log Models

Model Name	Net Effect of Daylight	Group F-Test
Natural log 10-months	+5.7%	>0.01
Natural log 24-months	+1.1%	>0.005

Table 1 shows that the average net effects for the daylight interaction variables as a group (Daylight Hours, Parking*Daylight Hours, and Age of Store*Daylight Hours) are positive for both models, and that the interaction variables are all significant as a group (group F-test). In other words, the log models predict a chain-wide average increase in sales associated with the presence of daylight of 1% to 6%. This average effect is, however, not large enough in either case to give a high enough level of certainty that it would not dip down below zero if we considered a different population of stores in our analysis. A larger population of study sites (for example, doubling the number of sites from 73 to 150) would have provided greater statistical power, and would have likely provided greater certainty in the analysis.

Daylight Effect Interaction with Parking

In all of our models, we found that the *daylight hours*parking* interaction variable was significant. This means that, for whatever reason, the daylight effect was being modified by the amount of parking available at each store site. As explained above, we calculated a net daylight effect for each store site, based on the value of the parking scalar and daylight hours variable for that site.

In order to understand the theoretical impact of the daylighting effect independent of the parking interaction variable, we held parking constant. We performed this exercise at three levels—the norm for the daylit stores, and the norm plus or minus the standard deviation of parking for the daylit stores—and then predicted the net daylight effect for the group of daylit stores, as shown in Table 2. When parking is one standard deviation greater than norm, the daylight effect jumps up dramatically to +20%. When parking is restricted, the daylight is seen to have a negative effect. The nature of the linear equations used in the regression models forces one end of the range to go negative when the other end is strongly positive, something like a see-saw. Thus, there is less certainty about the high or low ends of the predicted effect than the norm.

Table 2. Daylight Effect Independent of Parking, Log 10-month Sales, 2001

Condition	2001
Parking @ norm	+5.6%
Parking @ 1 std. dev. below norm	-8.7%
Parking @ 1 std. dev. above norm	+19.7%

Table 2 suggests that the daylighting effect may have its greatest advantage when there is sufficient parking to take advantage of the additional demand created.

Daylight Effect as a Function of Daylight Hours

Once we understood the interaction of parking with daylighting effect, we looked at the predicted daylight effect as a function of increasing daylight hours per store, holding the size of the parking lot constant. This analysis showed that there is clearly a relationship between more hours of daylight per store and a greater daylight effect on sales. This is a clear dose/response relationship, which says that as the number of daylit hours increases, the relative effect on sales also increases.

The results for this analysis suggest "bounds" for a daylight effect. These predictions are illustrated in Figure 2 and Figure 3. (Note that in Figure 3 the scale for one graph, "1999-2000 parking at mean model," has a much smaller vertical scale than the others..) When parking is held at norm, as in the plots on the left, the daylight effect varies from a low of –2% to a high of +14% increase in sales per store. In these equations, the amount of parking becomes a limiting factor. When we allow parking to increase up to a higher level, as in the plots on the right, one standard deviation above the norm, the prediction of the daylight effect per store ranges from +2% to +37%. In all cases, as the number of useful daylight hours per year increases, the relative daylight effect on sales also increases. This sensitivity analysis could be considered as describing the bounds of a daylighting effect on sales, varying from none at all to a high of about 37%. This upper bound is consistent with the previous retail and skylight study that found a 40% increase in sales associated with skylights in that chain store (Heschong Mahone Group 1999a). The previous study did not consider parking as a potential explanatory variable.

Figure 2. Daylight Effect as a Function of Daylight Hours, Log 10-month Sales, 2001

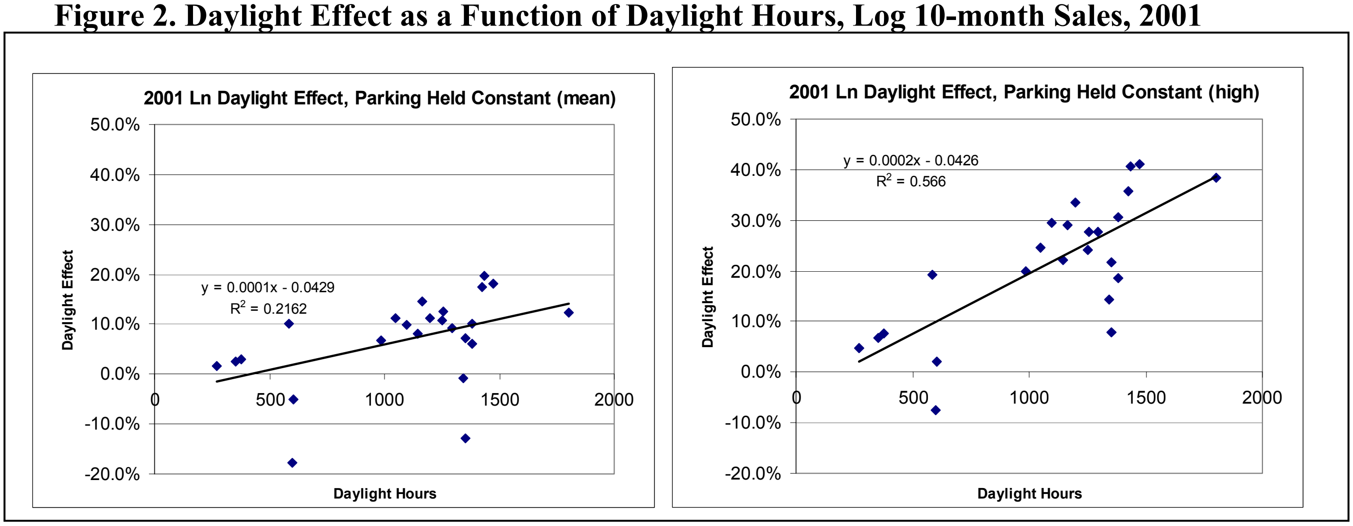
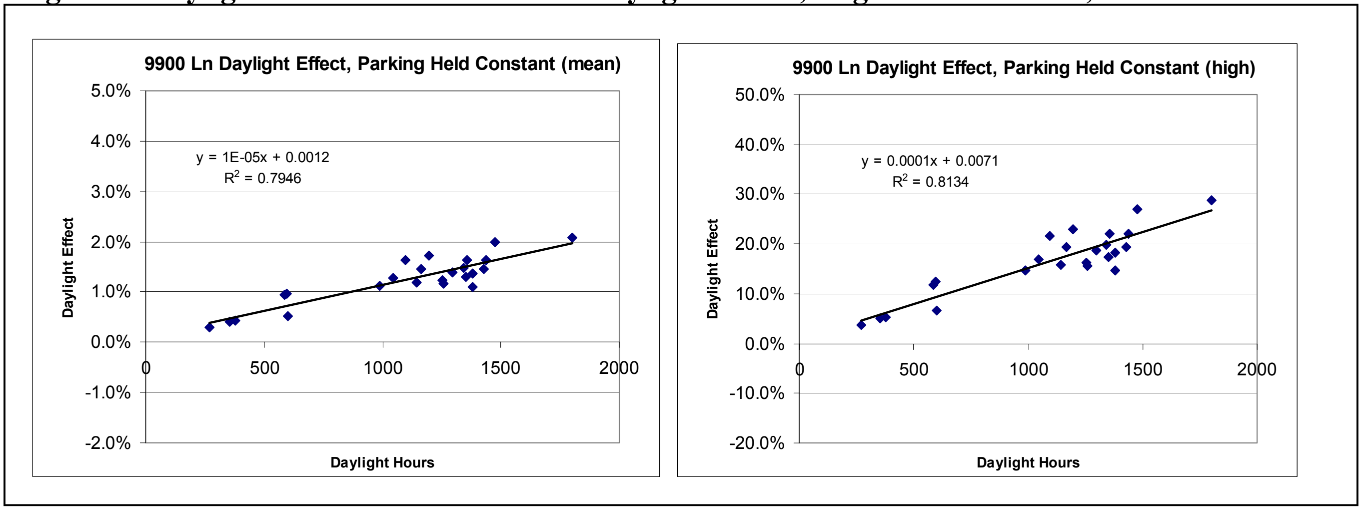


Figure 3. Daylight Effect as a Function of Daylight Hours, Log 24-month Sales, 1999-2000



Variable Partial R^2 and Order of Entry

The order of entry of variables into the model and the amount of variance explained by each variable (partial R^2) can be an important indicator of the relative importance of a variable in predicting an outcome. We show these statistics for the two log models in Figure 4 and Figure 5.

In both the log and the linear models, the age of the store is consistently the most important predictor of sales for this chain, explaining from 28% to 38% of the variance in the sales data. All of the rest of the variables in the model are considerably less robust, predicting less than 8% of the variance, and often less than 1%. In this context, it is interesting to note that the daylight hour variable tends to be a reasonably powerful predictor of sales (4%-5%), consistently at least as strong as, if not stronger than, the competition variables (3%-6%) and than the demographic variables from census data (1%-6%). Thus, these models strongly suggest that the amount of daylight in a store is equally useful in explaining sales potential as the more traditional characteristics—parking, competition and demographics—to which classic real estate analysis pays a great deal of attention.

Figure 4. Order of Entry and Partial R^2, Log 10-month Sales, 2001

Model Name: LN 01			
Variable Description	**Variable**	**Order of Entry**	**Partial r^2**
ln(Total Area)	logArea	2	0.069
ln(Age)	logAge	1	0.379
Transportation variable, 1990	Transport	12	0.026
Education variable 1990	Education	11	0.009
Number of sister stores within certain radius	Co-mktg	5	0.038
Number of competitor stores within radius 1	Compet 1	6	0.037
Storefront height scalar	Height	7	0.023
ln(Parking)	logPark	4	0.050
Outlier Store	out440	3	0.059
Daylit hours per year greater than threshold	DayHrs	9	0.038
Age * DayHrs	AgeDH	10	0.016
Parking * DayHrs	ParkDH	8	0.013

Figure 5. Order of Entry and Partial R^2, Log 24-month Sales, 1999-2000

Model Name: LN 99-00			
Variable Description	**Variable**	**Order of Entry**	**Partial r^2**
ln(Total Area)	logArea	2	0.077
ln(Age)	logAge	1	0.340
Transportation variable, 1990	Transport	8	0.015
Education variable 1990	Education	9	0.055
Number of sister stores within certain radius	Co-mktg	6	0.037
Number of competitor stores within radius 1	Compet 1	3	0.055
Storefront height scalar	Height	7	0.041
ln(Parking)	logPark	5	0.041
Outlier Store	out440	4	0.045
Daylit hours per year greater than threshold	**DayHrs**	**11**	**0.039**
Parking * DayHrs	ParkDH	10	0.004

Comparison of 10-month and 24-month Time Periods

It is interesting to consider why the daylight effect observed for the 10-month period was consistently larger than for the 24-month period. There are at least two possible explanations for this finding, which we will call the "contrast" hypothesis, where daylit stores gain in comparison to sister stores, and the "competitive" hypothesis, where daylit stores are more likely to gain competitors' business.

On the one hand, we separated the time periods in the analysis specifically because they had different lighting operation conditions. In the 24-month period (1999-2000) electric lights in the non-daylit stores were on at full power at all times, while lights in the daylit stores were controlled to respond to daylight. During the 10-month period (2001) the electric lights in all stores were at reduced levels, both day and night. As a result, there was a greater contrast in the average ambient light conditions between daylit and non-daylit stores during the 10-month period.

The contrast hypothesis suggests that the greater daylight effect observed during the 10-month period was partly caused by the greater contrast in illumination levels between daylit and non-daylit stores. If daylit stores are observed to be selling more than non-daylit stores during the power reduction, it might be tempting to argue the alternative: that the reduction in lighting power during the 10-month period "hurt" sales for the non-daylit stores. However, this does not seem to be the case since all stores in the chain increased their sales during the 10-month period. Something in the general economy (or perhaps, store management) seems to have increased sales for all participant stores.

The competitive hypothesis, on the other hand, focuses on differences *between* this chain and other chains, which are more likely to be important determinants of corporate success than differences *within* the chain. During the California power crisis of 2001 almost all retailers in the state agreed to operate their stores at reduced lighting power in order to conserve energy and reduce peak loads on the state electric system. As a result, not only the study participant but most of their competitors were also operating at reduced electric lighting levels. Under these conditions, the daylit participant stores were even more successful than the rest of their sister stores in the chain, where the daylit stores experienced on average approximately 6% higher sales than the rest of the stores in the chain, as shown in Table 1.

Energy Savings Findings

Energy savings were the primary motivation for both the original installation of skylights with photocontrols, and the one-half lighting power reduction during the 10-month study period. Both of these programs resulted in substantial dollar savings for the retailer. The retailer is very satisfied with the resulting energy savings and considers these savings to be an important reduction in operating costs affecting the bottom-line profitability for the chain.

We did not monitor operation of the photocontrols or the overall energy performance of whole building systems relative to the skylight impacts. We did however, calculate lighting and whole building energy savings using SkyCalc and DOE-2 computer simulation models of the daylit stores, and compared these findings to average energy expenditures for the retailer during the two time periods.

The lighting energy savings from the skylights and photocontrol operation tend to run from about 20% to 30% compared to electric lights on at full power, while the whole building (lighting and HVAC) energy dollar savings range from about 15% to 25%. These numbers all vary by climate, daylighting system and store design, and photocontrol settings and operation. The stores are not necessarily using optimized designs (i.e. state-of-the-art daylighting systems), so potential savings due to the daylight could be higher with different design choices.

We calculated the energy savings from the current design and operation and then gradually increased the optimum performance of the skylight and photocontrol system heading towards a theoretical maximum performance. We found that the current system (good) is saving about $.24/sf for an average store in the chain, while an improved system (better) using current best-practices could save about $.54/sf, and an optimum system (best) using state-of-the-art performance could save about $.66/sf at current energy prices. Thus, the current daylight design is saving about one-third of the maximum amount of energy that could potentially be saved from daylighting.

To compare energy savings to sales impacts, we also calculated the progressive increase in sales impacts due to an improved daylighting system, making conservative assumptions about the value of sales per square foot, and assuming a store with average conditions for both daylight and parking. We found that while the sales effect increased with an improved daylighting design since there would be more hours of useful daylight per year, the energy savings increased at an even faster rate. For the 24-month period, the ratio of the value of the daylight sales effect to the energy savings was 45 times at the "good" (existing) level, 22 times at the "better" level and 19 times at the "best" level. For the 10-month period the sales numbers increase dramatically, since a higher value was found for the daylight effect. Under the 10-month conditions the ratio of daylight effect on sales to daylight energy savings was 234 times at the good level, 124 times at the better level and 107 times at the best level.

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