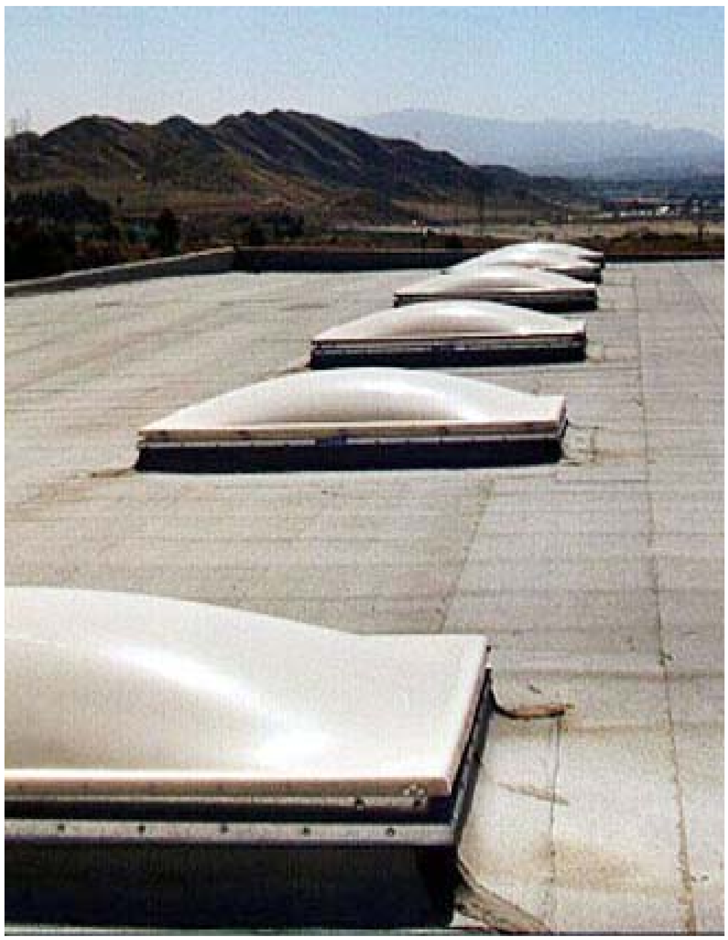
CALIFORNIA ENERGY COMMISSION

Daylight and Retail Sales



TECHNICAL REPORT

October 2003
P500-03-082-A-5

Gray Davis, *Governor*

CALIFORNIA ENERGY COMMISSION

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ACKNOWLEDGEMENTS

This report is a part of the Integrated Energy Systems - Productivity and Buildings Science program, a Public Interest Energy Research (PIER) program. It is funded by California ratepayers through California's System Benefit Charges administered by the California Energy Commission (CEC) under (PIER) contract No. 400-99-013, and managed by the New Buildings Institute. Heschong Mahone Group would like to acknowledge the support and contributions of the individuals below:

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Subcontractors: RLW Analytics, Inc: Dr. Roger Wright, RLW Analytics, Inc. statistical metholodies; Ramona Peet, analyst. Wirtshafter Associates: Dr. Robert Wirtshafter, census and GIS analysis

Review and Advisory Committee: Dr. Jed Waldman, California Department of Public Health; Dr. Gage Kingsbury, Northwest Evaluation Association; Dr. Judith Heerwagen, private consultant; Abby Vogen, Wisconsin Energy Center; Dr. Cliff Federspiel, Center for the Built Environment; Barbara Erwine, Cascadia Consulting; Dr. Robert Wirtshafter, Wirtshafter Associates, Inc.

Participant support: This project was supported by many managers and employees of the participant retail corporation. We are greatly appreciative of their time, facilitation and review of this study. Studies such as this are highly unusual, in that they require a leap of faith on the part of corporations that are traditionally highly private and protective of internal data. We have promised anonymity to this corporation, as we did with the previous study, and request that everyone involved will endeavor to respect that request and honor the trust placed in the study team.

PREFACE

The Public Interest Energy Research (PIER) Program supports public interest energy research and development that will help improve the quality of life in California by bringing environmentally safe, affordable, and reliable energy services and products to the marketplace.

This document is one of 33 technical attachments to the final report of a larger research effort called *Integrated Energy Systems: Productivity and Building Science Program* (Program) as part of the PIER Program funded by the California Energy Commission (Commission) and managed by the New Buildings Institute.

As the name suggests, it is not individual building components, equipment, or materials that optimize energy efficiency. Instead, energy efficiency is improved through the integrated design, construction, and operation of building systems. The *Integrated Energy Systems: Productivity and Building Science Program* research addressed six areas:

- ***Productivity and Interior Environments***
- ***Integrated Design of Large Commercial HVAC Systems***
- ***Integrated Design of Small Commercial HVAC Systems***
- ***Integrated Design of Commercial Building Ceiling Systems***
- ***Integrated Design of Residential Ducting & Air Flow Systems***
- ***Outdoor Lighting Baseline Assessment***

The Program's final report (Commission publication #P500-03-082) and its attachments are intended to provide a complete record of the objectives, methods, findings and accomplishments of the *Integrated Energy Systems: Productivity and Building Science Program*. The final report and attachments are highly applicable to architects, designers, contractors, building owners and operators, manufacturers, researchers, and the energy efficiency community.

This Daylighting and Retail Sales Report (Product # 2.3.7) is a part of the final report within the Productivity and Interior Environments research area and presents the results of a study into relationships between daylighting and sales at a retail outlet store.

The Buildings Program Area within the Public Interest Energy Research (PIER) Program produced these documents as part of a multi-project programmatic contract (#400-99-413). The Buildings Program includes new and existing buildings in both the residential and the non-residential sectors. The program seeks to decrease building energy use through research that will develop or improve energy efficient technologies, strategies, tools, and building performance evaluation methods.

For other reports produced within this contract or to obtain more information on the PIER Program, please visit www.energy.ca.gov/pier/buildings or contact the Commission's Publications Unit at 916-654-5200. All reports, guidelines and attachments are also publicly available at www.newbuildings.org/pier.

ABSTRACT

This study presents evidence that a chain retailer is experiencing higher sales in daylit stores than in similar non-daylit stores. Statistical models, using up to 50 explanatory variables, 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 study included 73 store locations in California, of which 24 stores were daylit primarily by diffusing skylights. Statistical regression models found that increased annual hours of useful daylight per store were strongly associated with increased sales, but at a smaller magnitude than a previous study. No season variation in the relationship of daylight to sales was found. The study also included interviews with store managers and surveys of employees, along with an analysis of the energy savings due to automatic control of the electric lights.

Author: Lisa Heschong, Heschong Mahone Group

Keywords: Daylight, Productivity, Retail, Sales, Stores, Window, Skylight, Design

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EXECUTIVE SUMMARY

This study presents evidence that a major retailer is experiencing higher sales in daylit stores than in similar non-daylit stores. 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 will remain 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.

This study was performed as a follow-on to a similar study completed for Pacific Gas and Electric in 1999[1], which found that for a certain retail chain, all other things being equal, stores with skylights experienced 40% higher sales than those without skylights. This study, on behalf of the California Energy Commission, examined a second retail chain, in an entirely different retail sector, to see if the original findings would hold in a new situation, and if we could learn more about any daylight effect that might exist.

As a first step in this process, a simple model with daylight as a yes/no variable, and using basically the same format and inputs as the previous study, did not find a significant correlation between the presence of daylight, and increased sales. We then pursued the study in greater detail, adding more information to the model and describing daylight on a continuous scale by the number of daylit hours per year in each store.

The retailer in this study had a less aggressive daylighting design strategy and also more variation in both the range of daylight conditions and the range of store designs than the retailer in the first study. For this study, we collected much more detailed information about the characteristics of each store, and verified all information on site. Neighborhood demographics and retail competition were described using detailed, site-specific GIS analysis. Store managers were interviewed and employees were surveyed about their observations and preferences. For the final analysis, the amount of daylight in each store was described as the number of hours per year that daylight illumination levels exceeded the design electric illumination level.

Statistical regression models of average sales for the stores, using up to 50 explanatory variables, and both linear and natural log descriptions of the variables, found that increased hours of daylight per store were strongly associated with increased sales, but at a much smaller magnitude than the previous study. In addition, for this chain, the daylight effect on sales was found to be constrained by the amount of parking available at the store site. Sites with parking lots smaller than the norm experienced decreased sales associated with daylight, while stores with average and ample parking experienced increased sales as both the amount of daylight and parking increased. The statistical models were also more comprehensive, explaining about 75% of the variation in the data (model R^2=0.75), compared to 58% in the previous study.

[1] Heschong Mahone Group (1999). Skylighting and Retail Sales. An investigation into the relationship between daylight and human performance. Detailed Report for Pacific Gas and Electric Company. Fair Oaks, CA.

Specifically, this study found that:

- Average effect of daylighting on sales for all daylit stores in this chain was variously calculated from 0% to 6%, depending on the type of model and time period considered.
- A dose/response relationship was found, whereby more hours of useful daylight per year in a store are associated with a greater daylight effect on sales.
- No seasonal patterns to this daylight effect were observed.
- A bound of an empirical daylight effect for this chain was detailed, with a maximum effect found in the most favorable stores of about a 40% increase in sales. This upper bound is consistent with our previous finding.
- Daylight was found to have as much explanatory power in predicting sales (as indicated by the variable's partial R^2) as other more traditional measures of retail potential, such as parking area, number of local competitors, and neighborhood demographics.
- Along with an increase in average monthly sales, the daylit stores were also found to have slightly smaller increase in the number of transactions per month.
- The retailer reported that the primary motivation for the inclusion of daylight was to save on energy costs by having photocontrols turn off electric lights when sufficient daylight was detected. The retailer has been very pleased with the resulting reduction in operating costs. Based on current energy prices we estimated average whole building energy savings for the daylit stores at $0.24/sf for the current design, with a potential for up to $0.66/sf with a state-of-the art design.
- The value of the energy savings from the daylighting is far overshadowed by the value of the predicted increase in sales due to daylighting. By the most conservative estimate, the profit from increased sales associated with daylight is worth at least 19 times more than the energy savings, and more likely, may be worth 45-100 times more than the energy savings.
- During the California power crisis of 2001, when almost all retailers in the state were operating their stores at half lighting power, the stores in this chain with daylight were found to benefit the most, with an average 5.5% increase in sales relative to the other non-daylit stores within the chain (even while <u>all</u> stores in this chain increased their sales compared to the previous period).
- Employees of the daylit stores reported slightly higher satisfaction with the lighting quality conditions overall than those in the non-daylit stores. Most strikingly, they <u>perceived</u> the daylit stores to have more uniform lighting than the non-daylit stores, even though direct measurements showed both horizontal and vertical illuminance levels in the daylight stores to be substantially less uniform.
- Store managers did not report any increase in maintenance attributable to the skylights.
- The chain studied was found to be saving about $0.24/sf per year (2003 energy prices) due to use of photocontrols, which could potentially increase up to $0.66/sf per year with an optimized daylighting system.

1. INTRODUCTION

The Skylighting and Retail Sales study[1] completed in 1999 by the Heschong Mahone Group on behalf of the California Board for Energy Efficiency found a compelling statistical correlation between the presence of daylighting in a chain retail store and higher sales for those stores.

The 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,[2] that could only be addressed in follow-up studies.

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?

4. **Investigating temporal effects or other causal mechanisms:** If we found positive sales associated with daylighting in another retail chain, could we determine if it had a seasonal nature, associated with longer hours of daylight in the summer, or a daily effect, associated with more intense levels of daylight during the middle of the day? Alternatively, might a positive daylight effect be related to increased customer loyalty, improved employee moral, or some mechanism less tied to temporal variation in daylight availability?

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[1] Heschong Mahone Group (1999). Skylighting and Retail Sales. An investigation into the relationship between daylight and human performance Detailed Report for Pacific Gas and Electric Company. Fair Oaks, CA.

[2] Heschong Mahone Group (1999). Daylighting and Productivity. An investigation into the relationship between daylight and human performance. Review Report. Fair Oaks, CA.

The study described in this report, supported through the California Energy Commission's Public Interest Energy Research (PIER) program, 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 retailer provided us with dimensionless monthly sales index data for each store for a 34-month period. The research team then identified 73 store sites appropriate for the study, one-third with daylighting, and collected extensive data about each site.

The research team's information about each store site was used in a statistical regression model, and for secondary analysis. This information included:

1. Information about the size, age, history and monthly sales volumes of the stores (from corporate sources)
2. Population characteristics within a radial distance of the stores (from U.S. Census 1990 and 2000)
3. Number of competitors within a radial distance of the stores (from public databases)
4. On-site observations about the neighborhood and about the stores' architectural features, skylighting system, lighting, mechanical systems, and other site-specific conditions.
5. Interviews and surveys with store managers and employees.

This data was processed and put into a multivariate regression model. A number of modeling approaches were investigated. Monthly data allowed us to look for seasonal patterns. Two different electric lighting conditions during the study period allowed us to examine illumination intensity issues. Although we were not allowed to interview customers, interviews with store managers and surveys of store employees allowed us to examine attitudes and perceptions associated with daylighting. A range of daylighting conditions within the participant's store sites allowed us to probe for a dose/response relationship between daylighting and sales.

Finally, the analysis results were studied, and conclusions were drawn about the role of daylighting in the sales of this retail chain. This report describes the data and analysis methodologies in greater detail. Conclusions are then presented in Chapter 8. The Appendices include the data collection forms and other study details, as well as a brief glossary of statistical terms to assist readers who are less familiar with the statistical methods utilized by this study.

2. SELECTION OF STUDY PARTICIPANT

Selection of a participant for a large statistical study is a very important and strategic investment. We invested a considerable amount of time and effort to find the most promising retail corporation to study for our second effort at understanding how daylight might effect retail sales patterns.

2.1. Selection Criteria

Prior to beginning the search for a participant retail store, we determined a set of ideal characteristics that we would use to evaluate and qualify the candidate retail stores. The following criteria guided our selection process. They were intended to maximize the potential significance of the study and to minimize confounding factors.

At a minimum, the retail store selected for this study would:

1. Be a **large chain retailer** with consistent building size, merchandising practices, merchandise layout and product selection across its stores.

2. Have a **large number of stores** in relatively small geographical region. The strength of the statistical analysis is directly related to the number of store sites studied, so the chain would ideally have at least one hundred sites available for study. The closer these stores are to each other, the lower the data collection costs would be for on-site visits, and the more likely that the stores will have similar climate profiles.

3. Have **some daylit and some non-daylit stores** so that daylighting effects could be compared between otherwise identical environments. It would be ideal to have a continuous range of daylighting conditions so that a dose-response relationship between daylighting and sales could be studied.

4. **Maintain a database** on the performance of each store. This information would most likely be sales data, but could be other metrics of store performance. The finer the grain of the sales data in terms of time period or sales department, the more detailed the analysis we would be able to do. Similarly, if the participant could provide data on the characteristics of the individual store locations, we would be able to invest project resources in other types of data collection and thus conduct a more precise analysis overall.

5. Be **willing to participate**. The research could not proceed without the corporation's permission to utilize their sales tracking data and to allow us to physically inspect their buildings. Enthusiasm for the study was likely to facilitate and expedite such access.

6. Be willing to **allow the study results to be published publicly**. As a project funded with public goods moneys from the State of California, we are obligated to make our findings public. If the participant preferred to remain

anonymous, we could accommodate this request with careful attention to confidentiality issues, but the results would be published.

In addition, other desirable, but not required, characteristics included:

7. Allow us to **collect data at each store location**, if necessary, to complete our data gathering process. It was unlikely that all of the information necessary to control for other influences on performance would be available in the existing data. Therefore, we were likely to need to collect additional data on site.

8. Have **little variation between daylit and non-daylit** stores other than the amount of daylight available. This would minimize the number of other factors that needed to be controlled for.

9. Be a **different retail sector** than the original participant. A specific goal of this project was to study a retail participant in a different market sector than the previous study, so that we could start to understand the range of applications where daylighting may have an effect and bound the magnitude of those effects.

10. Allow us to **interview store customers** to understand how customer perceptions and attitudes toward the store relate to the productivity of each location. In the absence of direct customer interviews, alternative approaches to collecting customer reactions could be considered.

11. Allow us to **interview store personnel**. Obtaining the opinions of store employees could be in addition to, or as an alternative to, interviewing customers and could help us understand influences on store performance from a wider perspective.

2.2. Participant Search

The above selection criteria provided us with a basis for deciding the appropriateness of various candidate retail participants. Our search for participants involved reviewing library information, examining web-based resources and conducting interviews with potential candidate stores. Our research identified about a dozen chain stores as potential study sites, who we then interviewed about their interest in participating in the study.

Our initial search process resulted in four candidate chain stores that expressed interest in the study and met our basic criteria. We referred to these four potential participants as Retailer A, B, C and D. We then interviewed each candidate more closely about the implications and potential for participation. We particularly focused on the number of stores with and without skylights, the variety of daylighting conditions and the presence of any confounding factors, especially the presence of any obvious store characteristics that might be collinear with the presence of skylights at particular store locations, such as higher ceilings only in skylit stores, or skylights only in new stores.

Each of the four chain stores had very different characteristics of skylight distribution and store design issues. The corporate history of the chains also varied widely. Two participants, Retailer A and B, showed the most potential for study.

The team discussed the possibility of doing two studies, each with less depth, in order to increase the diversity of the study. We received initial site characteristics data from both candidates and visited a sample of sites from both retailers. From the initial site reconnaissance, we concluded that Retailer B had some particularly confounding variables that we would not be able to fully control for in our statistical analysis. Retailer A seemed to have fewer confounding issues, and more data available about store performance, history and design characteristics. At this point, Retailer A allowed us to review store plans, and provided additional information that reassured us about the feasibility of the study. We finally decided to work with Retailer A on the study and expressed our appreciation to the others for their interest.

2.3. Participant Description

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. The participant met all of the above minimum selection criteria (numbers 1-6) and all of the 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. These were all located in California. Of the sites included in the study, all but two were single story buildings. Twenty-four of the 73 sites had some form of daylighting, primarily with diffuse 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 felt we might be able to treat the presence of daylight as a scalar variable, rather than as a yes/no variable as in the previous study.

3. DATA COLLECTION

Data collection for the study proceeded from a number of sources. First we collected as much information as possible from the retail participant directly, from corporate records, plan rooms, and interviews with corporate managers. We then conducted on-site surveys of every store to be included in the study, to confirm information from the corporate records and to collect new, detailed data about the physical conditions at each store. Next we collected and processed Census and market conditions information from various public databases, using GIS analysis to create site specific information. Finally, we analyzed interviews with store managers and surveys of store employees to gain a more qualitative understanding of the conditions at each store.

3.1. Corporate Databases and Records

The retailer maintained databases that included each site's location, age, size of building and sales areas in square feet, number of product lines, monthly sales, and number of sales transactions. They provided us with this data, including 34 months of the monthly sales data.

The retailer also maintained a reference set of miniature architectural plans, aerial photos, and other construction and maintenance records. These were examined for each site to determine the layout of the sales floor, the length of street frontage, the number of parking spaces, and in most cases, the ceiling height and the lighting system type and layout. We were also able to review lighting maintenance records to determine the most recent relamping period for each store and other operational details. Two surveyors reviewed the plans and filled out a Plan Review Survey Form.

3.2. Corporate Interviews

From telephone and in-person interviews, 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 between skylighting and store sales performance.

We learned that the retailer had a wide variety of ownership/tenant relationship 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.

We also probed for other site variables that the retailer thought were likely to particularly affect sales performance. This information helped us to decide what additional information we should try to collect about the sites in order to control for other influences on sales.

3.3. On-site Visits

Based on the assessment of available data, we determined that we would need 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 would be allowed to interview the store manager and ask the manager to have employees complete a simple lighting quality survey.

3.3.1. Surveyors and Training

Three surveyors, who were all were permanent employees of the Heschong Mahone Group (HMG), collected the on-site data. All of the surveyors were architecturally trained and had a background in daylighting. The surveyors wore neutral colored clothes such as khakis to minimize influence on the light meter readings.

The surveyors practiced the survey methods together in an initial store that was part of the chain, but not part of the study. They discussed the interpretations of each field in the survey data collection form, and practiced finding the standard locations for photos and instrument readings. In addition to the standard photograph locations, surveyors were encouraged to take additional photographs to help explain any unique conditions found at a store. Throughout the on-site survey period, surveyors met periodically to discuss findings and the survey instrument to aid in the normalization of results.

A generic version of the survey instrument is included in the Appendix, providing more specifics on the format of on-site data collection.

3.3.2. Survey Equipment

The surveyors used the following equipment:

Clipboard with:

> **Floor Plan**: an 8.5 x 11" Xerox of the store floor plan(s)
>
> **Plan Review Survey Form**: copy of the plan review survey for each store, both for reference and verification or completion.
>
> **Site and Manager Survey Forms**: blank site and manager survey forms
>
> **Authorization**: Letter of permission to visit site from retailer headquarters

Camera: a Toshiba PDR-M70 digital camera.

Light Meter: a hand held Minolta TL-1 Illuminance Reader. Illumination readings were taken in footcandles; A 10x filter allowed for outdoor daylight readings. Only one illuminance meter was used to avoid calibration inconsistencies.

Thermometer: a hand held digital dry bulb and temperature meter for taking dry-bulb temperature readings, in degrees Celsius.

Anometer: hand held meter for taking air movement readings in ft/min.

Decibel meter: hand held meter for taking ambient noise level readings in dBA.

Flicker Checker: a spinning tool from Motorola for checking for the presence of electronic flicker in the lighting.

Tape measure: to measure dimensions not found in the plan review.

3.3.3. Survey Protocol

Upon receiving permission from the store manager to start the survey, the surveyor took the initial outdoor horizontal illuminance reading and exterior photos at designated locations. The surveyor then also made other exterior site observations about the neighborhood conditions, building signage, size of the main street, visibility from the main street and sky conditions at the time of the survey.

Next, the surveyor confirmed information about the store that had been collected from the earlier review of corporate records and/or shown on the plan. Interior building information recorded included surface reflectance observations, luminaire characteristics, skylight characteristics, thermal environment and acoustic environment. In addition, illuminance measurements were taken, and several photographs were taken from standard vantage points to document building conditions.

Four sets of illuminance measurements were taken at the check out area and the primary, secondary and back aisles of the store in order to quantify the variety of lighting conditions in the store. At each location, the hand-held measurements included a horizontal measurement at 4 feet in the center of the aisle (typical shopping cart and display height), and vertical measurements on the face of the product at 2 feet, 4 feet and 6 feet on each side of the aisle (heights easily managed by the surveyors without use of aids). In skylit stores, the aisle measurement sets were doubled, with one set taken as directly underneath a skylight as possible and one set taken in between two skylights. The goal was to quantify the maximum range of illumination conditions found in the store. This procedure was slightly modified from the Lighting Baseline Study of 25 California Retail Stores[1]. All other readings, such as temperature and noise readings, were taken at the center of the store.

At the conclusion of the survey, the surveyor took a second reading of exterior illumination levels. The average of the entrance and exit readings were later used to normalize the interior daylight readings.

Site visits were scheduled during non-peak sales periods and were completed within 30 to 60 minutes. Visits to skylit stores were preferentially 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 within an eight-week period, from late January to early March of 2002.

The fact that not all site visits were conducted during the same time of day or week made some site observations more suspect. For example, the surveyor observed noise levels and perceptible air movement, but these observations are likely to be a function of time of day and the intensity of customer activity at the time of observation.

Upon completion, a copy of all photographs and on-site data collection was provided as a service to the retailer for their records.

[1] Heschong Mahone Group, *Lighting Baseline Study*, for Southern California Edison, 2000. Presented at the IESNA conference 2001, Ottawa Canada.

3.3.4. Manager Interview

The short interview with the store manager offered an opportunity to collect information about a store that would not be readily apparent from the corporate records or a site visit. For example, we asked if there had been any disruptions to sales in recent history, due to nearby construction, natural disasters, power outages, or other intermittent events. Similarly, the store manager was usually in a position to tell us about the recent arrival of competitors in the neighborhood or about special attributes of that particular store or location that we might not otherwise notice.

Store manager interviews were kept confidential and not provided to the retailer.

3.3.5. Lighting Quality Survey

Finally, we developed a lighting quality survey to be administered to the employees of each store. This survey was modified from a lighting quality survey originally developed by Dr. Peter Boyce at the Lighting Research Center for office settings. It was subsequently modified to a retail and school format for the Lighting Baseline Study[1] sponsored by Southern California Edison. That study collected baseline lighting quality data on 25 examples each of existing, newly constructed California office spaces, classrooms and retail stores. Those studies found that the survey, which asked only yes-no questions, tended to be somewhat insensitive, with all respondents rating their lighting above average. Therefore the survey was revised, with responses requested on a 1-7 scale instead. The question wording remained the same.

The lighting quality survey forms were handed out by the manager to 20 to 30 retail sales staff at a convenient time. The lighting quality survey forms were returned to HMG via a self-addressed stamped envelope. We ultimately received an average of 18 responses per store.

3.4. Census Demographic Data

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 stores, only achieved 95% significance as a predictor of store sales performance, and together only explained 3% of the variation in the data. Our goal was to use better demographic predictors of store sales in the current study.

Current practice in the field of real estate location analysis uses US Census data within either a fixed radius or a calculated drive time from a proposed store location. Drive time analysis is often considered the best analysis available. Global Information Systems (GIS) maps that have up-to-date streets and drive times allow a computer to map out the distances from any location that take, say, 10 minutes to drive at normal traffic speeds. Such a calculation allows accurate comparisons of residents within an accessible distance of an urban store site surrounded by slow surface streets and a suburban store site located off of a fast highway.

[1] Heschong Mahone Group, *Lighting Baseline Study*, for Southern California Edison, 2000. Presented at the IESNA conference 2001, Ottawa Canada.

Our goal was to create a reliable comparison between sites in our study as a control variable, rather than pre-determine the most favorable location for a new store. An initial comparison of a few store sites in our study showed that the simpler fixed radius analysis captured population effects within 85 to 90% accuracy of the far more complex drive-time analysis. In addition, we noted that many of our store sites were located in rapidly developing areas where street information was not up-to-date in the GIS databases. Thus, we determined that using a fixed radius Census analysis would give us sufficient accuracy, and perhaps also a more reliable comparison between our sites. We interviewed the real estate manager for the chain and determined the appropriate radius to use in the census analysis. This is henceforth called the "standard radius."

We reviewed 34 possible census characteristics with the real estate manager for 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. We will not identify the specifics of the census variables considered in order to protect the retailer's identity. 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.

3.5. Local Market Analysis

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 one standard radius and twice the standard radius of each site. We used a simple count of store locations within a fixed radius, rather than a more sophisticated "gravity" analysis, which attempts to account for floor area and volume of other competitors relative to distance from a given location. Since competitor stores tended to be fairly standardized, this provided acceptable accuracy. This information formed two additional variables considered in the analysis: *Compet 1* (number of competitors within one standard radius) and *Compet 2* (number of competitors within two standard radii).

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.

Interviews with store managers revealed if there had been any event in the neighborhood that might have dramatically impacted sales during the time period of the study. This included such things as major construction nearby which interfered with customers' access, or a nearby fire or other disaster that affected sales. This information was converted to a flag variable that indicated a negative sales event for that store.

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 with 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 out the stores in the study 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.

3.6. Data Verification

The data from the site visits was collected on paper survey forms, then entered into electronic databases, with standard error bounds testing and validation features. The data was checked and processed within Microsoft Access, and then transferred into SAS for statistical analysis.

All of the site data was examined to make sure that it was reliable and provided a sufficient range of conditions for useful analysis. The acoustic, dry bulb air temperature and air movement instrument readings were found to be inconsistent, and frequently out of bounds, and so were dropped from the analysis. Surveyor observations about noise sources and perceptible air movement were found to be more believable and consistent and were used in their place.

3.7. Parking Data Verification

During the course of analysis it was discovered that some of the parking lot counts collected in the initial plan review phase of data collection did not seem plausible. Many of the site plans reviewed were old or incomplete, and it was possible that the parking lot had been modified since the plan date. Since the parking lot variable was quite significant in initial models of sales performance, we decided to verify the parking lot counts during the study period.

We obtained parking lot counts from the retailer for about 80% of the store sites. However, these counts were of uncertain dates and based on a variety of counting methodologies. We also obtained low-resolution aerial photographs for about 80% of the sites (not the same 80%), from which we could estimate the parking capacity of the lots. While the aerial photos were considered the most reliable in terms of time period (they were all from approximately the study period) they were often difficult to interpret.

After consideration of a number of methodologies, we created a method to select between the available information sources for a given store. This method is described in Appendix 9.3. This process resulted in about 25% of the parking counts being revised. As a result of this process the parking data was brought into a more normal range. This data was re-entered into the models, and forms the basis of our final reports.

4. DATA PROCESSING AND VARIABLE DEFINITION

Upon completion of data collection and verification, the data was processed into useful variables for analysis. If a store characteristic did not exhibit sufficient variation between stores, we could not use it in the analysis. For example, the variety of signage was not found to vary much between survey sites, and so signage type was not considered in the analysis. Likewise, whenever fewer than four stores exhibited a particular characteristic, that characteristic was dropped from the analysis.

In some cases data was combined in order to increase the range of variation in the data for analysis. For example, the acoustic properties of the stores were originally collected according to five different properties, but they were subsequently combined into one acoustic scalar indicating overall noise levels in the stores. Similarly, we were given data on the square footage and number of products sold for a variety of sales areas. We first collapsed this information into three types of sales areas, and eventually collapsed it into a variable named “total sales area scalar.”

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.

Descriptive statistics for the variables considered in the analysis are included in the Appendix. These include the minimum, maximum, range, mean and standard deviation for that variable. When a scalar variable is used, the minimum is a dimensionless unit of one, and the maximum illustrates the relative range of that variable.

4.1. Dependent, or Outcome, Variables

The retailer provided us with 34 months of monthly sales totals and number of transactions per store site. All these data were transformed into dimensionless scalars that would not reveal actual amounts, but that could be used consistently in statistical analysis, with different multipliers used for each type of data.

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. This voluntary reduction in light levels, by both retailers and other companies, had an enormous impact in helping to reduce the peak power demands in California that year, thereby helping to avert many potential rolling blackouts.

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.

For each of these two time periods, we analyzed the data with two mathematical approaches, using both linear and log models of the sales data. The transaction data were similarly broken into the two periods, but were only analyzed with linear models. Each outcome variable was considered in a separate regression model.

Outcome variables considered:

- **Sales24:** Sales index per store, the average of the monthly sales index for the 24-month period during 1999 and 2000
- **Sales10:** Sales index per store, the average of the monthly sales index for the 10-month period during 2001
- **Log Sales24:** Natural log of the sales index per store, the average of the monthly sales index for the 24-month period during 1999 and 2000
- **Log Sales10:** Natural log of the sales index per store, the average of the monthly sales index for the 10-month period during 2001
- **Trans24**: Transaction index per store, the average of the monthly transaction index for 24-month period during 1999 and 2000
- **Trans10**: Transaction index per store, the average of the monthly transaction index for 10-month period during 2001

4.2. Independent, or Explanatory, Variables:

Independent variables were considered in five basic groups: corporate level variables, census variables, local market influences, comfort conditions, and interaction variables. Below we describe each explanatory variable considered in the analysis and give the data source. The term “scalar” is applied to variables that have been transformed from the raw data into a dimensionless scale in order to mask information about the identity of the retailer Indented variables are variants of the one above, used in preliminary investigation or final log models. Summary statistics for all variables are described in Figure 21 and Figure 26 in the Appendix.

CORPORATE LEVEL DATA:

- **Area:** Total sales area scalar, the relative size of the sales area in each store, per corporate records
  - In preliminary analysis Area was broken into three sub areas, termed Sales Area 1, 2 and 3.
  - **LogArea**; Natural log of the total sales area scalar, used in log models
- **Hours**: Longer work week yes/no, indicator for a store with hours open longer than standard, per corporate records
- **Age**: Store age scalar, relative age of the store, per corporate records
  - **LogAge**; Natural log of the store age scalar, used in log models

- **Mgr**: Manager seniority scalar, relative seniority in corporation, reported by store manager

CENSUS DATA (all per standard radius from store location; census year indicated):

- **Housing**: Housing status, 2000
- **Pop**: Population density, 2000
- **PopGrow**: Population growth percentage, (2000-1990)
- **Ethnic**: Ethnic status, 2000
- **Household**: Household status, 2000
- **Income**: Income status, 1990
- **Econ**: Economic status, 1990
- **Education**: Education status, 1990
- **Language**: Language status, 1990
- **Transport**: Transportation status, 1990

LOCAL MARKET INFLUENCES (source indicated):

- **Co-mktg**: Number of sister stores within standard radius, GIS analysis
- **Compet 1**: Number of competitor stores within standard radius, GIS analysis
- **Compet 2**: Number of competitor stores within twice standard radius, GIS analysis
- **Cotenant**: Co-tenant scalar, a scale of 0-4 for co-tenants, based on estimated intensity of customer visits to co-tenant, observed by surveyor
- **Lanes**: Number of lanes on the main street, observed by surveyor
- **Visible**: Street visibility scalar, relative visibility of store from primary frontage street, on a scale of 1-4, observed by surveyor
- **Sign**: Building signage yes/no, signage for store is typical or atypical, observed by surveyor
- **Event**: A negative sales event in neighborhood, yes/no, reported by store manager
- **Length**: Storefront length scalar, relative length of storefront visible to frontage street, taken from plans
- **Height**: Storefront height scalar, relative height of highest part of store frontage, taken from plans
- **Parking**: Parking scalar, relative number of parking spaces, taken from plans, corporate data and aerial photos (see Appendix for data source selection method)

STORE COMFORT CONDITIONS

- **DayHrs**: Hours of daylight above a certain illumination threshold, as derived from annual SkyCalc or DOE-2 simulations based on store design and climate location (discussed in next section)
  - Daylight, yes/no (significant daylight in store, other than from entrance façade glass), used in preliminary investigations
  - Daylight, partial area illuminated, yes/no, used in preliminary investigations
  - Daylight, from vertical glazing, yes/no, used in preliminary investigations

- **VertAvg**: Average of all vertical illuminance readings, a measure of intensity of illuminance (normalized for outside illuminance at time of measurement in daylit stores), per site measurements
- **VertSD**: Standard deviation of all vertical illuminance readings, a measure of uniformity of vertical illuminance levels, per site measurements
- **Luminaire**: Atypical luminaire yes/no, standard luminaire layout for retailer or atypical, observed by surveyor
    - Lamps: Type of lamps, standard or atypical, used in preliminary investigations
- **Lightson**: Electric lighting scalar, relative scalar of portion of electric lights on during study period, based on corporate records and on-site observations
- **Ceiling**: Ceiling height scalar, relative average height of ceiling, taken from plans
- **Air**: Noticeable air movement yes/no, observed by surveyor
- **Smell**: Odor scalar, relative presence of pleasant or unpleasant smells in store, observed by surveyor
- **Noise**: Noise scalar, relative distracting noise levels in store, observed by surveyor
- **Clean**: Cleanliness of store scalar, observed by surveyor

INTERACTION VARIABLES (interaction variables with daylight hours were tested for all variables that were significant in preliminary models)

- **AreaDH**: Sales area scalar times daylight hours
- **AgeDH**: Store age scalar times daylight hours
- **PopGrowDH**: Population Growth times daylight hours
- **MktgDH**: Number of sister stores times daylight hours
- **Comp1DH**: Number of competitors within radius 1 times daylight hours
- **HeightDG**: Store maximum height scalar times daylight hours
- **FrongtageDH**: Store length scalar times daylight hours
- **ParkDH**: Parking area scalar times daylight hours
- **AreaDHhours**: Store area scalar times daylight hours times longer work week yes/no

4.2.1. 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 site 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 design horizontal illumination in non-daylit stores reported to us by the store management (which was also empirically found to be very close to the observed average horizontal illumination in non-daylit stores). This 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, based on building design variables, local climate using typical meteorological year data (TMY2), type of glazing, amount of glazing area, dimensions and surface reflectances within the store. This was fairly easy for the standard skylit stores, using our 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.[1]

The SkyCalc daylight hour calculations are limited by the granularity of TMY weather data available for each site that could be used to generate input. There are 16 climate files available for SkyCalc in California, based on the 16 climate zones defined by the California Energy Commission for the Title 24 Building Energy Standards. Thus, the daylight availability analysis is for typical weather in a nearby city representing the appropriate California climate zone for each site, rather than actual yearly weather for a specific city or store site.

4.2.2. Energy Observations

Using this method to estimate store daylight system performance, we found that daylight availability above threshold conditions varied from a low of 270 hours per year, to a high of 1800 hours per year, with a mean of 1090 and a standard deviation of 409. There are a total of 4,380 daylight hours available per year (12 hrs * 365 days). Thus, this retailer was estimated to be reducing electric lighting in the daylit stores about 25% of the daylight hours.

We were not able to monitor actual practice. Simulation of these skylight systems suggested that these stores were far below optimum daylight performance. More aggressive daylighting design could have produced more hours of useful illumination, and more aggressive photocontrol operation (at a lower threshold) could also have produced far greater energy savings. A more optimized system could probably have reduced electric lighting in the daylit stores for about 75% of the daylit hours.

Further discussion of the energy impacts of the design and comparison to the daylight effect on sales is included in Section 7.1 Energy Impacts.

[1]For more information on SkyCalc, see: Heschong, Lisa and Jon McHugh, "*Skylights: Calculating Illumination Levels and Energy Impacts*," *Journal of the Illumination Engineering Society*, Winter 2000, Vol. 29, No. 1, pp. 90-100, and *Skylighting Guidelines,* 1999, a web-based publication on skylighting design, downloadable from www.energydesignresources.com.

5. STATISTICAL METHODOLOGY

The heart of this study was the statistical analysis of the data collected. This analysis entailed developing statistical models that seek 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 both science and insight. It 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 are used to determine which modeling approach provides the most mathematically accurate representation of the data. It is important to remember that the statistical models are a mathematical abstraction of reality. They do not so much provide true or false answers, as provide a way to simplify a very complex retail environment and start to quantify the relative magnitude and certainty of various influences on sales performance.

Regression models try to fit lines that best describe a plot of data points. Multivariate models consider more than one dimension at once. Linear models try to fit straight lines through the data. It is also possible, but far more complex, to consider curved, or non-linear, relationships, as we did with models using a natural log function.

All of the analysis was pursued using multivariate regression models run in SAS using a variant of backwards step-wise regression to eliminate the least significant variables. F-tests[1] 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 criteria for 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. All statistical terms are explained in Section 9.2 in the Appendix.

Models were judged based on their R^2 (the percentage of variation in the data explained by the model), the parsimony (minimum explanatory variables for maximum explanatory power), and consistency between the models. Ultimately, models predicting more moderate effects for daylight were also judged to be more realistic than those with wildly diverging values.

5.1. Variable Testing Method

There are 3 stepwise variable selection procedures that are often employed in linear regression: forward selection, stepwise selection, and backward elimination. The forward selection procedure starts with an equation that contains only the constant term and successively adds explanatory variables one-by-one, until the last variable added to the model is insignificant. Stepwise selection is essentially a forward stepwise procedure, with the exception that at each iteration, the possibility of deleting a variable is also considered.

[1] See Appendix Section 9.2 for an explanation of "F-test" and other statistical terms used in this report.

The backward elimination method first calls for fitting a model using all potential explanatory variables and calculating the t-statistic associated with each variable. The explanatory variables are then deleted from the model one-by-one, until all variables remaining in the model are associated with a significant t-statistic. During each iteration, the variable with the least explanatory power is identified and deleted from the model.

The RLW variable selection method[1], used in this study, is a variant of the backward elimination method. Similar to the backward elimination method, the RLW variable selection method begins with calculating a model using all potential explanatory variables and the associated t-statistics. However, the RLW method allows for the deletion of multiple variables during each iteration, whereas the backward elimination method does not. This procedure helps to identify co-linearities between insignificant variables, which might otherwise be dropped without first understanding how such co-linearities could potentially influence results. Specifically, the RLW method consists of the following steps:

1. Calculate a “full” linear regression model including all potential explanatory variables.
2. Identify all insignificant variables from the model resulting from step 1.
3. Perform an F-test to test whether the set of individually insignificant variables are statistically significant as a group. Specifically, the null hypothesis of the F-test is that the beta coefficients of each of the variables in the group are zero, while the alternative hypothesis is that there is at least one variable in the group where the beta coefficient is not zero. If the F-test shows the set of variables are not statistically significant as a group, all variables identified in step 2 are also identified for deletion. If the set of variables tested is statistically significant as a group, this indicates there is a collinear relationship between the variables that is affecting the model. In this case, a reduced set of variables is defined for the F-test and deletion from the model.
4. Calculate a reduced model including all explanatory variables that were not identified for deletion.
5. If any previously significant variables become insignificant in the reduced model, calculate an F-test for all variables previously deleted from the model and the newly insignificant variables under the guidelines provided in step 3.

[1] The RLW variable selection methodology was developed by Dr. Roger Wright, lead statistician of this study.

5.2. Preliminary Investigations

We began the statistical analysis with a number of preliminary investigations to help us identify appropriate variables and the best form of the model.

5.2.1. Defining the Core Model

We had a very long list of potential variables that we wanted to consider as explanatory variables in this study. To simply this process of identifying the most significant variables, we began by running simple models, first testing just the corporate level information, then adding the demographic and marketing 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. After a series of about four comparative runs, we settled on a core model with the highest R^2 and the most consistent set of explanatory variables. Figure 1 lists the variables significant in these core models, and their respective p-values.

"Core" Model, Significant Variables		($p \leq 0.10$)
	10 month	**24 month**
Sales Area 1	.018	.032
Sales Area 3	.036	.034
Longer Hours	.011	.003
Store Age	.000	.000
Population Growth	.008	.038
Population Density	.078	.053
Household Status	.085	.043
Sister Stores	.036	.013
Competitors, Radius 1	.016	.006
Height of Storefront		.053
Parking Scalar	.000	.000
Model R^2	**68.5**	**70.2**

Figure 1: "Core" Model Significant Variables

The models were tested for "outliers," or store sites that were performing significantly different from all the others, and therefore unduly influencing the findings. One store tested as an outlier and so was isolated from the equation. This store was a very high selling daylit store.

These two core models were then used to test various ways of defining the daylight variable and other physical conditions of the individual stores.

5.2.2. Simple Yes/No Daylight Model

First 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 physical comfort characteristics about each store. Figure 2 shows the p-values for significant variables in this model.

Daylight Yes/No Model, Significant Variables ($p \leq 0.10$)	**10 month**	**24 month**
Sales Area 1	0.018	0.069
Sales Area 2	0.036	0.019
Longer Hours	0.011	0.051
Store Age	0.000	0.001
Population Growth	0.008	
Population Density	0.078	
Housing	0.085	
Education		0.029
Transportation		0.037
# Sister Stores	0.036	0.019
Competitors, Radius 1	0.016	0.011
Frontage Height		0.027
Parking	0.000	0.000
Model R^2	**68.5**	**68.7**

Figure 2: Daylight Yes/No Model, List of Significant Variables

In these initial 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. The new census variables were significant, but were not consistent for both models. Likewise, the height of the storefront was significant in one model, but not both.

5.2.3. Daylight Hours Analysis

Our next set of investigations focused on creating a more precise way to model daylight, rather than using a simple yes/no indicator. The amount of daylight in a store varies in intensity through out the day and year. For simple skylit spaces, there is a fairly predictable relationship that the more intense the daylight is under peak conditions, the more overall hours of useful daylight there will be per year. Thus, as a measure of both intensity and duration, we chose to calculate the number of hours per year that the daylighting illuminance would exceed a certain threshold illuminance. We calculated this value for various illuminance thresholds. Ultimately, we used the target electric illuminance for the non-daylit stores as our threshold, as this variable provided the greatest discrimination in values across the daylit stores. This target illumination level was obtained from the management, and confirmed by measuring the average horizontal illuminance for non-daylit stores.

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 and higher average vertical illumination levels 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 outcome variable, as described below, which highlighted those variables most strongly correlated with daylight. Second, we identified a set of interaction variables for inclusion in the final models, which accounted for interaction effect between the presence of daylight and other significant variables in predicting the sales index.

Identifying Variables Co-Linear with Daylight

In order to understand the magnitude of the collinearities between the daylighting variable and the other explanatory variables under consideration, we calculated a linear regression model where the outcome, or dependent, variable was the number of daylight hours. We allowed all of the information we had about the stores to compete in the models we tested, and we found that these models explained 70% of the variation in daylight hours predicted per store. Variables significant above the 90% level ($p \leq 0.10$) included:

Significant Variables Predicting Daylight Hours

	($p \leq 0.10$)
Sales Area 2	0.058
Competitors, Radius 2	0.022
Length of store front	0.034
Average of all vertical illuminance	0.000
Electric lighting scalar	0.000
Type of lamps	0.034
Cleanliness of store	0.062
Ceiling type	0.000
Model R^2	**70.5**

Figure 3: Daylight Hours as Outcome Variable

The good news from this exercise was that none of variables that had shown up as predicting sales in the “core” models were significant in predicting the daylight hours, thus they were determined not to be collinear with daylighting.

The bad news from this exercise was that there were clearly many potential explanatory variables that were collinear with daylight hours. In addition to those shown above, a quick test told us that there were many other variables that were collinear with daylight hours, but below the model threshold 90% significance level. All of these collinear variables could potentially cause problems in our subsequent sales analysis, confounding the effect of the daylight variable on the sales index. This was likely to be the greatest concern for explanatory variables that were also significant predictors of sales.

A number of these collinear variables had a logical relationship to the presence of daylight, such as the ceiling type, which was almost a yes/no indicator for daylight, or higher vertical illuminance levels, which was almost universally higher in daylight stores. When there were such obvious dependencies between variables related to daylight levels, we ran the variables in separate sales index models, testing which of the competing variables had more significance and predictive power. In these tests, the daylight hours variable stayed in the model as significant and the other descriptors dropped out as not significant. Thus, we concluded that daylight hours, rather than other correlated conditions, were more useful predictors of sales. Therefore, we left the other variables out of our subsequent models.

While we can never be certain that excluded collinear variables are not influencing the daylight hour results, we have higher confidence in the daylight hour variable for two reasons. First, per above, it provided more precision in predicting a sales effect. Secondly, there was a more obvious hypothesis for a causal relationship.

For similar reasons, at this point we also dropped the electric lighting scalar, type of lamps, and cleanliness of store variables. We did not have confidence these variables were reliable. The electric lighting scalar was based on observations at the time of the survey, but the lighting could easily have been different during the other times of the study period. The type of lamps variable was based on conflicting evidence from a number of sources, and may also have changed during the study period. The cleanliness variable had a very limited range of conditions between stores, and was also rather subjective. We have seen in our previous study that shoppers tended to associate daylighting with a cleaner store, and it seemed possible that our surveyors may have made the same assessment.

Daylight Interaction Variables

To control for the effects of the co-linearities observed above, we created a model that considered interaction variables between the daylighting variable and all explanatory variables that had been retained as significant throughout the preliminary tests of models.

We were especially concerned that *Sales Area 2* was collinear with skylighting, even through it was not showing up in the core models as a significant predictor of sales. Two versions of the interaction model were tested – one where the different sales areas and associated interactions were considered separately and one that considered the aggregate of the various sales areas (total sales area) and an interaction variable between it and daylighting. The models that considered the different sales areas separately were generally somewhat illogical, inconsistent and un-interpretable, while the variant using the total square footage was more stable and easily interpreted. Both versions had almost identical explanatory power. For this reason, we selected the variant of the model that was based on the total sales areas.

The use of interaction variables made for more precise models, but also made them a bit more difficult to interpret directly. With interaction variables, the effect of more daylight in the stores can only be understood relative to the other influences on the daylight effect. Interaction variables basically describe second-order effects, which modify the primary effects of the two variables considered. When using interaction variables, if one interaction variable is found to be significant, then all of its component parts are also forced into the model, whether they are significant or not, so that the net effect can be properly calculated. In the case of one of our models, the 10-month linear sales model, two daylight variables were kept in the model, even though they fell below the threshold significance level of $p \leq 0.10$.

It is important to recognize that the models using Daylight Hours with interaction effects are far more complex than the 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 Daylight Hours models with their interaction variables, on the other hand, predict a varying range of effects, per individual store, as a function of each store's unique combination of physical conditions. The predicted daylight effect per store is calculated by applying the model's equation to each store's specific characteristics relative to its daylight hours and interaction variables. Thus, this calculation includes the effects of total daylight hours as predicted by local climate conditions, store surface reflectances, skylight area, etc, and the daylight interaction variables included in that model, such as parking area or age of the store.

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. When we calculated this net effect for the chain for each model, we found a net positive effect for three of the four models. These values are reported in the Findings, Section 6.1.

5.2.4. Demographic Test

Somewhat surprisingly, very few, and often only one, of the 10 demographic variables were found to predict sales in these preliminary models. We hypothesized that two of the other explanatory variables, which measured the amount of competition within the area, were absorbing all of the market effects that would be normally predicted by demographic information.

For example, if both the study retailer, and all of its competitors, were carefully and consistently analyzing demographic information in order to select new store sites, then the number of sister and competitor stores within a certain radius would already predict most of the demographic variables. To test this theory, we ran another series of models, dropping the sister store and competitor store explanatory variables. When we did this, two more demographic variables, which characterized the local population's economic status, did indeed enter the models at high significance. The R^2 of these models, however, were slightly lower, convincing us that our two "competition" variables did indeed do a better job of capturing demographic effects.

5.3. Final Regression Models

The mathematics of the regression models can take different forms, depending on the kind of effect one is trying to study. 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 log[1] 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 seemed appropriate.

Using the natural log of the outcome variable basically puts the Y-axis on a log scale with diminishing effects as one moves up the scale. This is illustrated in the diagrammatic graphs shown in Figure 4, which plots the same data on the two different scales. Figure 4 shows that for a log model, a unit change in X value at the low end of the range makes a bigger difference in Y, than the same change in X value at the high

[1] a logarithmic function based on the natural number "e"

end of the scale. A log model thus makes sense when one expects there to be a case of diminishing returns, where a unit increase in an explanatory variable at the bottom of the scale is expected to have a proportionately bigger effect than at the top. For example, one might hypothesize that doubling the size of a parking lot will have a relatively greater effect for a small 50 space lot than a large 500 space lot.

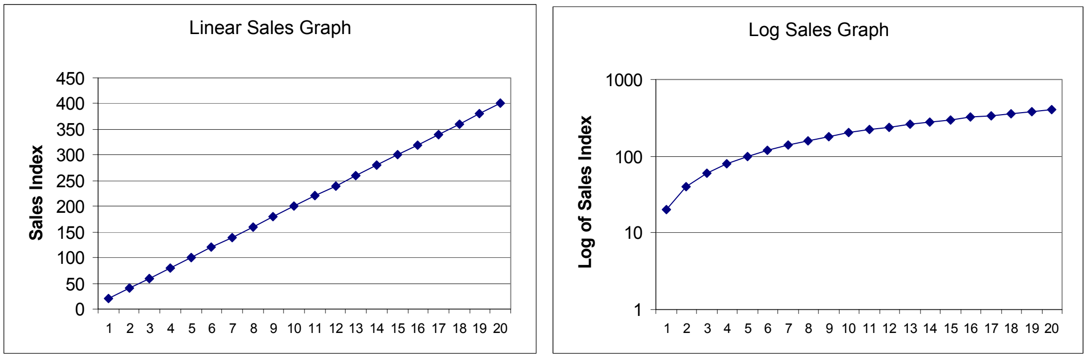

Figure 4: Diagrammatic Graphs of Linear v Log Scales

We tested models using natural logs of both the dependent variable (sales) and of some of the explanatory variables that seemed appropriate for a logarithmic scale. A logarithmic function requires that the variable be defined on a continuous scale, and also that it does not include any values less than or equal to zero, since the natural logarithm function is only defined for positive numbers. Thus, only some variables can be converted to natural logarithms. In addition to meeting the mathematical criteria for taking the log of a variable, a logged variable should also have a logical explanation for why a diminishing effect might be expected as the scale of the variable increases.

Using these criteria, we took the natural log of the following explanatory variables and included them in a "log" model of the Sales Index: Sales Area, Store Age, and Parking. When we did this, the number of significant interaction variables was also reduced, suggesting that taking the log of these variables was doing a better job of accounting for the interaction effects than the explicit interaction variables. In the log models, only the *parking*daylight hours* interaction variable remained significant.

5.3.1. Comparison of Linear versus Log Models

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 the models is quite high[1]. For the linear models it is 74% (24m) and 80% (10m). In other words, the models are explaining 74-80% of the variation in sales among the stores studied. This is considerably more than our previous retail study, which achieved an R^2 of 58%.

The R^2 of the log models is in a similar range. However, it is not appropriate to compare the R^2 of linear versus log models, since the outcome variables are not defined on the same scale. An appropriate comparison between models of this type was developed by statisticians called the "Box-Cox Transformation".

[1] See Appendix 8.3 for an explanation of the R^2 expression.

A Box-Cox comparison was run between the linear and the natural log models. Using this method, it was 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 comparing the models including the parsimony of the models, the consistency between the two time periods, and the reasonableness of the predicted effects.

- PARSIMONY: The log and linear models were found to be equally parsimonious. In both cases the 10 month models used 11 variables and one outlier and the 24 month models used 10 and the same outlier. The log and linear models had degrees of freedom of 62 and 59 respectively.
- CONSISTENCY: The log and linear models were found to be equally consistent in their predictions of a daylight effect per store site between the two time periods. This is illustrated visually in Figure 6, which shows a very consistent pattern of predicted daylight effects between the two time periods for both types of models.

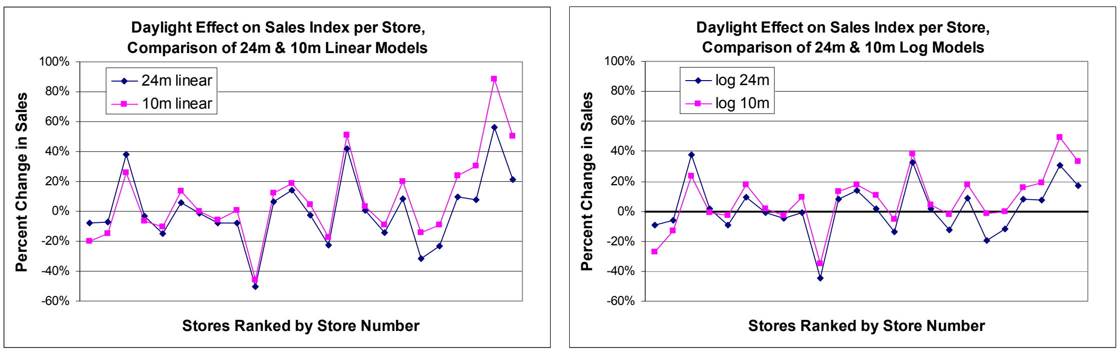

Figure 5: Consistency of Daylight Effects – Linear vs. Log Models

- MODERATE EFFECTS: The log models predicted slightly more conservative daylight effects across the range of daylit stores than the linear models. This is illustrated in Figure 6, which shows the difference in predicted daylight effects between the log and linear models for the two time periods. Figure 7 reports on the numerical ranges between the minimum and maximum daylight effects predicted by the various models. The 24m and 10m log models had predicted ranges that were 77% and 63% respectively of the linear models.

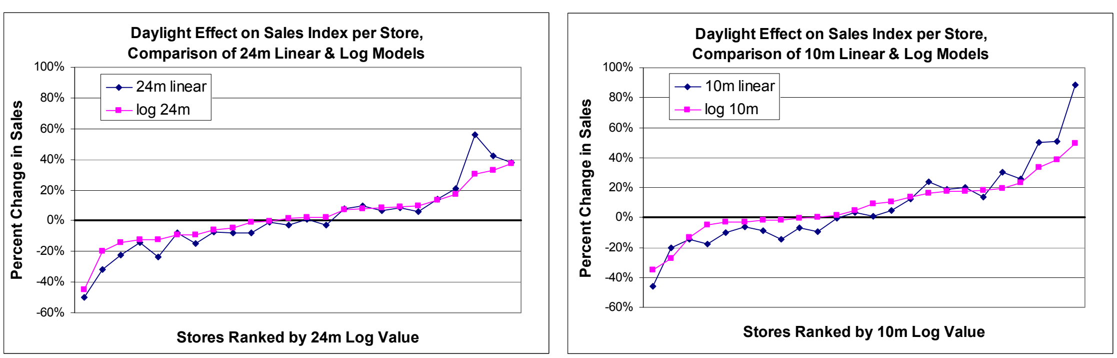

Figure 6: Comparsion of Daylight Effects per Store – Linear and Log Models

Model Name	Min Effect	Max Effect	Range of Effects
24 m Linear	-50%	56%	106%
24 m Log	-45%	37%	82%
24m Log range as a percent of 24m Linear range			77%

Model Name	Min Effect	Max Effect	Range of Effects
10 m Linear	-46%	88%	134%
10 m Log	-35%	49%	84%
10m Log range as a percent of 10m Linear range			63%

Figure 7: Range of Daylight Effects per Store predicted by Linear v Log Models

Based on the secondary criteria of a more moderate range in prediction of effects, we selected the logged models as the preferred models of the daylight effects of this retailer, and so the logged models are considered first with greater detail in analysis. The results of both types of models, however, were remarkably similar and so we will present the findings about the net daylight effects of both the linear and log approaches in the next section.

6. ANALYSIS FINDINGS

In this section we report on the findings primarily from the log models and secondarily, the linear models. The full equation for each model, and the descriptive statistics for all the variables considered in the model, are detailed in the Appendix.

As mentioned earlier, some of the variables have been converted into "scalars" in order to preserve the anonymity of the participant. In all cases, these scalars were created using simple division or multiplication as appropriate, so that they are statistically consistent.

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 summed 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.

It is not really appropriate to calculate a standard deviation for these findings, since they are not based on one yes/no variable, but a multi-dimensional group of variables. In order to express the range of the potential effect of daylight on an individual store, we have plotted the range of predicted effects for the two models in Figure 9 and Figure 17, below. It is important to note that the models do not predict a positive effect for every individual store. Some stores are predicted to have lower sales associated with daylighting, based on the effects of the interaction variables.

We performed an additional statistical test to consider the certainty of the net effect predicted by the combination of interaction variables. We used an F-Test to test the null hypothesis that the beta coefficients of each of the interaction variables in the group are simultaneously zero. The alternative hypothesis is that there is at least one variable in the group where the beta coefficient is not zero. The groups of interaction variables were found to be significant in all models, and so remain in our final models.

6.1. Log Models

The log models had consistent explanatory variables for both the 10-month and the 24-month versions, except for one additional interaction variable in the 10 month model. The magnitude of each variable's effects and significance are also quite similar. The R^2 of the log models are 74.7 and 75.7 respectively. 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.

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%	

Figure 8: Results of Log Models

Figure 8 lists the variables this model found to be 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. Other variables with positive effects include the age of the store, the number of sister stores nearby, and a more educated local population.

In a linear model, a one-unit change in the explanatory variable (X) predicts an approximate constant, or *fixed*, unit change (B) in the sales index (Y). So for example, if the size of the store increases by one square foot, then the sales index will go up by *B*. In these log models, a one-unit change in a non-logged explanatory variable predicts an approximate *percentage* change in the sales index. And for logged explanatory variables in the log model, a *one-percent* increase in the explanatory variable predicts an approximate *percentage* 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 then sales index is increased 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 are taken into account. In order to express the range of the potential effect of daylight on an individual store, we have plotted the range of predicted effects for the two Log models in Figure 9 below.

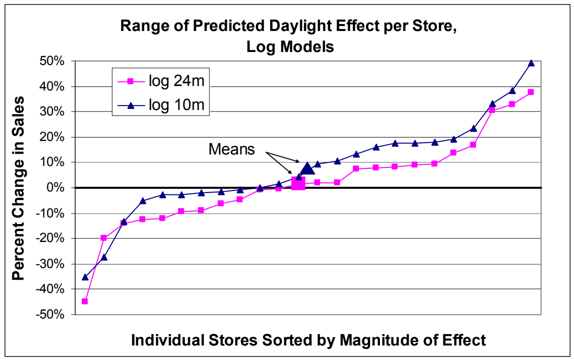

Figure 9: Graph of Predicted Range of Daylight Effect per Store, Log Models

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 per Figure 10 below:

Model Name	Net Effect of Daylight	group F-test
Natural log 10 months	**+5.7%**	>.01
Natural log 24 months	**+1.1%**	>.005

Figure 10: Net Effect of Daylight on Sales, Log Models

Figure 10 shows that the average net effects for the daylight interaction variables as a group are positive for both models, and that the interaction variables are all significant as a group (group F-test). This average effect is, however, not large enough in either case to give 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.

Thus, the log models predict a chain-wide average increase in sales associated with the presence of daylight of 1% to 6%.

6.1.1. 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.

Figure 11 plots the predicted daylight effect for each store as a function of its parking area relative to the norm. It is clear from this graph that as available parking area increases the predicted daylight effect also rises. The daylight effect starts to go negative when parking is reduced to 90% or less of the norm for the chain.

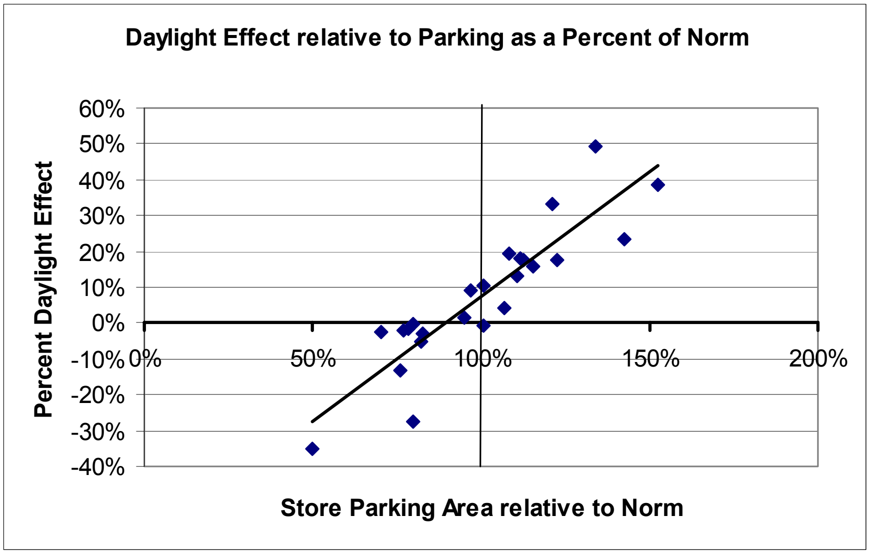

Figure 11: Daylight Effect relative to Parking Area

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 Figure 12. When parking is 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.

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

Figure 12: Daylight Effect Independent of Parking, Log 10 Month Sales, 2001

Figure 12 suggests that the daylighting effect may have its greatest advantage when there is sufficient parking to take advantage of the additional demand created.

6.1.2. 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 2001 model suggests that, when parking is held constant at the mean, for every increase in 100 daylight hours per year per store, the daylight effect increases by 1%, ranging from a low of -2% to a high of +14%. When parking is held constant at a high level (the mean plus one standard deviation), then for every increase in 100 daylight hours per year per store, the daylight effect increases by 2.4%, ranging from +2% to +37%. These predictions are illustrated in Figure 13.

In the 1999-2000 model, when parking is held constant at the mean, an increase in 100 hours of daylight increases the daylight effect by 0.1%, ranging from +0.4% to +2.0%. When parking is held constant at a high level (the mean plus one standard deviation), then for every increase in 100 daylight hours per year per store, the daylight effect increases by 2%, ranging from +5% to +27%. These predictions are illustrated in Figure 14. (Note that in Figure 14 the scale for one graph, “1999-2000 parking at mean model,” has a different vertical scale, 1/10 the size of the others, in order to show detail in the smaller effects seen in this example.)

The results for these plots suggest a “bounds” for a daylight effect. When parking is held at norm, the daylight effect varies from a low prediction 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, 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.

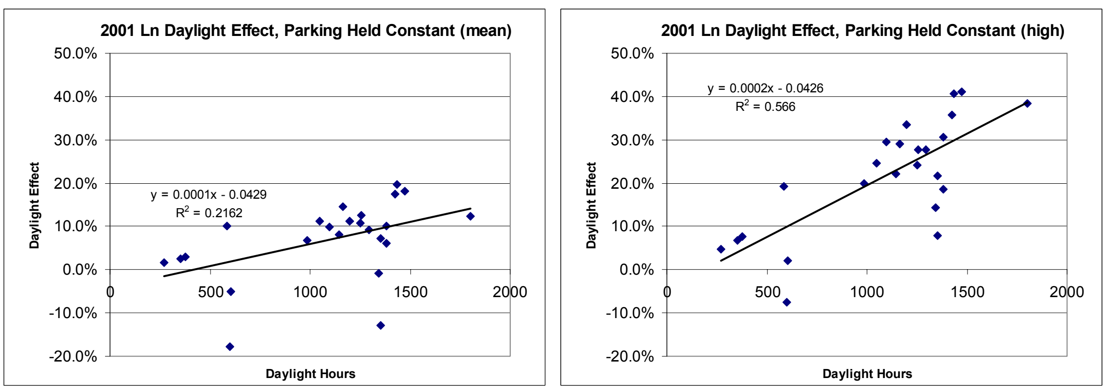

Figure 13: Daylight Effect as a Function of Daylight Hours, Log 10 Month Sales, 2001

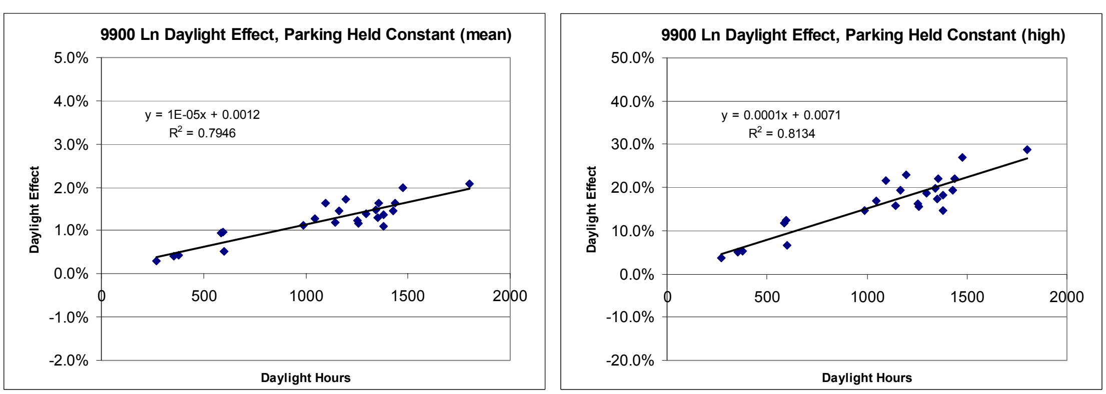

Figure 14: Daylight Effect as a Function of Daylight Hours, Log 24 Month Sales, 1999-2000

6.2. Linear Models

For completeness we present the findings of the linear models for comparison to the log models described above.

The linear models had the same set of explanatory variables as the log models, consistent across both the 10 month and the 24 month versions, and the same additional interaction variable in the 2001 model.

The R^2 of the linear models are 76.5 and 75.3 respectively. Thus, again we are explaining about 75% of the variation in the sales data between stores, while 25% remains unexplained due to other factors, or is just random variation. As explained earlier in Section 5.3.1, the R^2 of log and linear models cannot be compared directly, since their outcome variables are on different scales. A comparison was done via a Box-Cox transformation, and the explanatory power of the two equations was found to be essentially identical.

Model Name: Linear 01		
Variable	**B**	**Sig.**
Area	1052	0.002
Age	147	0.000
Transport	-0.038	0.010
Education	0.009	0.007
Co-mktg	181	0.001
Compet 1	-122	0.006
Height	-416	0.007
Parking	-579	0.000
Out44	2183	0.000
DayHrs50	-1.41	0.002
AgeDH	-0.08	0.089
ParkDH	0.73	0.000
Model Summary:		
RMSE	440	
R^2	76.5%	

Model Name: Linear 99-00		
Variable	**B**	**Sig.**
Area	1305	0.000
Age	111	0.000
Transport	-0.064	0.000
Education	0.013	0.000
Co-mktg	217	0.000
Compet 1	-130	0.006
Height	-389	0.019
Parking	-517	0.000
Out44	1982	0.000
DayHrs	-1.57	0.001
ParkDH	0.64	0.001
Model Summary:		
RMSE	475	
R^2	75.3%	

Figure 15: Results of Linear Sales Model

Here the B-coefficients for the *Daylight Hours* variable are again negative, but once the effect of the interaction variables are taken into account, the net daylight effect becomes positive in the 10 month model. In the 24 month model it is found to be effectively zero, as described in Figure 16 below. In order to express the range of the potential effect of daylight on an individual store, we have plotted the range of predicted effects for the two linear models in Figure 17 below.

The linear models find that adding daylight to stores (based on the norm of the corporate design, or about 1090 hours of useful daylight per year) will be associated with the following increase in sales:

Model Name	Net Effect of Daylight	group F-test
Linear 10 months	**+5.2%**	>.0001
Linear 24 months	**-0.3%**	>.005

Figure 16: Net Effects of Daylight on Sales, Linear Models

Figure 16 shows that the predicted net effects are positive for the ten month model, but slightly negative (or essentially zero) for the twenty-four month model. The interaction variables are all significant as a group (group F -test) in both models, and so were retained as a group. The linear and log models thus have essentially the same prediction: that during the 10 month period during 2001 daylit stores increased their sales relative to non daylit stores by 5-6%. During the 24 month period during 1999-2000 the daylit stores were found to be selling at very similar levels to the non-daylit stores (i.e., 0% to 1%).

In order to express the range of the potential effect of daylight on an individual store, we have plotted the range of predicted effects for the two linear models in Figure 17 below.

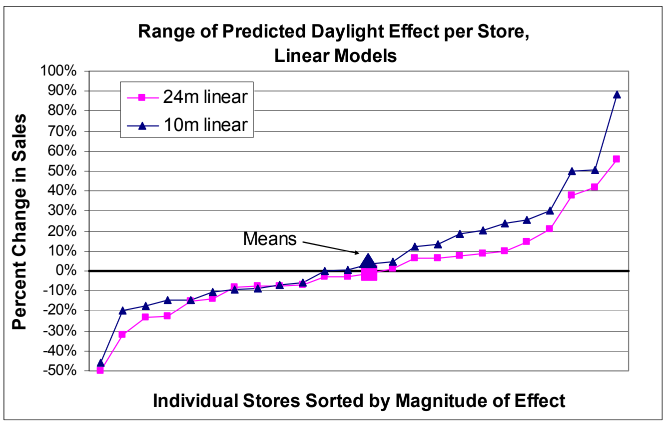

Figure 17: Graph of Predicted Range of Daylight Effect per Store, Linear Models

Given the similarity of results, we did not attempt to describe the effect of daylight independent of parking, as we did above with the log models.

Again, per the discussion in the log models, this average effect is not large enough to give certainty that it would not dip down below zero (in the case of the ten month model) or rise above zero (in the case of the twenty-four month model) if we considered a different population of stores in our analysis. A larger population of study sites (say doubling the number of sites from 73 to 150) would have been helpful to provide greater certainty in the models' predictions.

6.3. Discussion of Findings

These statistical models are substantially more complex than considered in the previous study, and give less dramatic results. However, we actually have higher confidence in this analysis, given the amount of attention given to verifying details of the data, and testing alternative hypotheses. The smaller magnitude of the predicted daylight effect is actually closer to what one would intuitively expect. Indeed, the very size of the prediction of the previous study (that daylit stores were selling 40% more than non-daylit stores) made it subject to criticism and disbelief.

This analysis has also provided us with a rich field of information that has allowed us to extend the results into more detailed consideration of the implications of daylighting and illumination on sales.

6.3.1. Variable 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 our four models in the Appendix in Figure 24, Figure 25, Figure 29, and Figure 30.

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%. The size of the store and the amount of parking tend to be the two next most powerful variables, at partial R^2 = 5-8% and 4-8% respectively. It is interesting to note that the daylight hour variable tends to be the next most 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%). This means that information about the amount of daylight hours in a store is doing at least as good of a job, if not better, of explaining variation in store sales than information about the number of nearby competitors or the population demographics of the neighborhood.

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.

6.3.2. Comparison with Previous Study

The retailer in this study had a less aggressive daylighting design strategy and also substantially more variation in both the range of daylight conditions and the range of store designs than the retailer in the first study. On the one hand, the greater range of conditions, combined with a smaller number of study sites, would suggest that we would not be as successful in predicting the influences on sales as with the previous participant, who maintained greater uniformity in their operations. On the other hand, the greater range of information and the presumed greater accuracy of the information, given the attention to site verification, would suggest that we should have greater success in predicting influences on sales. The R^2 of the models suggest that the second trend was stronger, as the models of this study explain about 75% of the variation in the sales data compared to 58% in the previous study.

The attempt to replicate the format of the previous model was most likely unsuccessful because of two characteristics of the stores in this study. First of all, the average daylight effect was observed to be much smaller, i.e. closer to zero, and therefore less likely to be found significant in a simple yes/no model. The greater sensitivity of a scalar description of daylight, describing the number of hours per year of daylight above a certain threshold helped to provide better resolution of the relationship between daylight and sales.

Secondly, for this particular chain there seems to be an important interaction between the amount of parking and any daylight effect. We do not know why this is so – we can only hypothesize based on common sense why such an interaction might occur. There is also always the possibility that this statistical interaction is simply a random occurrence of how the types of stores are distributed in the data. In the previous model we had no information about the amount of parking available at the various stores. Parking was not considered as an explanatory variable in the original model. Thus, we have no way to compare this parking-daylight effect with information from the previous participant.

The use of the daylight hours variable in this set of models has allowed us to detect a more subtle effect of daylight on sales, and also to describe a dose/response relationship between more daylight and more sales. This dose/response relationship is inherently more useful information to designers. It basically says that "more is better." It is not simply the presence of daylight at some threshold level, but progressively increased exposure that is most useful. It is unclear, however, from this analysis whether the increase has to do with more hours of useful daylight or higher levels of daylight illumination, since the two go hand in hand and we cannot distinguish between the two characteristics in the stores we studied.

6.3.3. Comparison of 10 Month and 24 Month Time Periods

It is interesting to consider why there was a significant daylight effect observed for the 10 month period and not 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 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 contrast hypothesis focuses on the differences between sister stores within the same chain. But, from the corporation's perspective, each store site is more importantly competing with the competitor's stores. Differences *between* this chain and other chains 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 the chain.

The competitive hypothesis suggests that under favorable economic conditions, the daylit stores in the study were even more attractive relative to the competitors' options than the non-daylit stores. Could it be that when shoppers are motivated to buy more products from the participant, they are even more motivated by the daylit stores? 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 the chain.

Because both events—the overall favorable economic conditions and the reduced lighting levels—seem to have happened simultaneously, we cannot distinguish between possible effects. Research into economic conditions that may have supported one these hypotheses was outside the scope of this report. Of course, other possible differences may exist between the two time periods that we did not observe or consider.

6.3.4. Other Findings

The details of the four models are shown in the tables in the Appendix. In simple English, the models tell us that the following variables, out of all of those we considered, are the best predictors of how much a given store operated by this retailer will sell:

- Bigger stores sell more
- Stores that are open longer hours sell more (or stores that sell more, are chosen to stay open longer)
- The older the store, the more it sells
- When the local population spends more time commuting to work, the lower the sales
- When the local population is more educated, the higher the sales
- The more sister stores within a certain radius, the higher the sales for all
- The more competitors within a certain radius, the lower the sales
- The higher the store front, the lower the sales
- The more parking spaces, the lower the sales
- The more hours of useful daylight per store per year, when combined with ample parking, the higher the sales

In understanding these model predictions, it is just as important to look at which explanatory variables were not found to predict sales. Somewhat surprisingly, only 2 of the 10 demographic variables tested were found to reliably predict sales. We conducted a test, described in Section 5.2.4, to see why this was the case. It was fairly clear that other variables that described the competitive environment—number of sister stores and number competitors within a certain radius—were already accounting for most of the demographic influence on sales.

It is also interesting, that of all the information we gathered on-site about the physical conditions of the stores, only daylighting was found to be reliably significant. Specifically, luminaire type, air movement, odors and noise were not found to predict sales. It could be that there was not enough variation between stores on these characteristics for meaningful analysis. Indeed, this chain makes great efforts to promote uniformity among stores. It could also be true that the conditions of these variables that our surveyors observed were not consistent over time or that we did not define the measurement protocol sufficiently accurately to define the response. Other variables associated with daylight, such as ceiling height, ceiling type, and vertical illumination levels, were also found to be positive and significant in earlier models, but *daylight hours* was found to be a better predictor then each of them, so they were dropped from the final models.

Storefront Height and Parking

In reviewing these results, the two results most controversial and counter-intuitive for the corporate managers were that higher storefronts and more parking were associated with reduced sales. They believe that higher storefronts and more parking should increase sales. Thus, they proposed that our findings for these variables might be a function of collinear effects with age or location. However, when we checked for interaction between these variables and age or demographics, the results still held. The storefront and parking variables are quite robust, and appeared highly significant in every model we have tried.

Alternatively, we propose that these findings might be a function of corporate decisions made relative to perceived competition in the area. When a site is perceived to have a great deal of competition from other chains that have high store fronts, then a new store site for this chain will be more likely to be designed with a high store front. Likewise, if competitors have very large parking lots, then a new store site with larger parking area would likely be preferred over a smaller site. Since these types of decisions would be made in a more competitive environment, it might be that they are associated with reduced sales due to the character of the local competition, rather than to a direct cause/effect relationship associated with the store front or the parking area.

Alternatively, it might be hypothesized that store sites with parking areas larger than norm were likely to be located in less successful shopping centers, for two possible reasons. One, lower pressure on land prices due to less retail activity might encourage the establishment of larger parking lots. Or two, highly successful shopping centers might be more likely to add additional stores to the complex, thereby reducing the availability of parking for the group of tenants as whole. Indeed, sites for future additional stores are often reserved in new shopping centers, but are maintained as overflow parking until the demand for new stores arises. Our methodology would not have distinguished the difference between normal (required) parking and parking areas designated for future store sites. Thus, less successful shopping centers are unlikely to fill in their extra store sites and therefore would be counted as having larger overall parking areas.

Interaction Variables

The interaction variables are also of interest. It was clear from the start of the study that this retailer had a much greater variety of store conditions than our previous study participant, and that a number of store characteristics were strongly associated with the presence of daylight. The interaction variables account for these interactions and moderate the effect of daylight relative to the presence of these other influences on sales that are correlated to daylight. The interaction variables certainly make for a more complex model, but also help us describe a more nuanced reality.

The interaction of parking with daylight hours is perhaps the least expected. As a simple variable, more parking, relative to all other variables, is seen to have a negative effect on sales. However, when we add in the interaction variable *parking*daylight*, more parking increases the positive effect of more daylight. This is true in both the log and linear models. This suggests that the negative effect of more parking is slightly overstated in the simple variable, and is moderated in the daylit stores.

6.4. Additional Analysis

We were able to perform some additional analysis to clarify secondary issues, using the same data sets. The following sections report on models which looked at potential seasonal variations in a daylight effect and a potential effect of daylight on the number of transactions per store.

6.4.1. Seasonal Effects

As part of our initial analysis, we also looked at the seasonal difference between daylit and non-daylit stores. This was first done simply by comparing the difference in monthly sales averages between the two types of stores. No other control factors were included. A plot of the difference in sales between the two groups of stores showed no obvious seasonal pattern. Indeed, it seemed to be rather random. There was no evidence of increasing or decreasing sales due to predictable changes in the climate, solar intensity, or outdoor temperature.

It was still possible, however, that a more sophisticated, multivariate seasonal analysis might turn up seasonal differences in sales performance between the two types of stores. To test this theory, we created a seasonal model using all of the variables considered in the sales models. Instead of yearly average sales indexes as outcome variables, we used the monthly average sales indexes for two extreme seasonal conditions—July and January—for all three years. July represents some of the longest, sunniest days of the year, and January represents some of the shortest, cloudiest days of the year. Using these two months also allowed us to avoid any anomalies due to the holiday period in December and include three years of observations for each season. This model included two additional types of explanatory variables; an indicator variable for each year and an indicator variable for month. These monthly models basically made the same predictions as the larger yearly models, with no hint of a variation in daylight effect between the two months. We reasoned that with no suggestion of seasonal variation between these two extremes, it was not worthwhile pursuing further efforts to find a seasonal effect.

Given our null finding of a seasonal difference in a daylight effect, we conclude that any "daylight effect" is more likely to be a result of long-term impact on overall customer loyalty, affecting sales through out the year, rather than a short-term boost in sales due to higher illumination levels or longer daylight hours.

6.4.2. Number of Transactions

Since we were given information about the number of transactions per store in addition to the value of sales, we decided to test the hypothesis that daylight increased sales by increasing the number of transactions rather than the value of sales per transaction. A transaction for this purpose is counted as one store visit per customer which resulted in sale of any number of items. Thus, an increase in the number of transactions at a store site could result from either an increase in the number of customers or an increase in the number of visits per customer, or both. As with the sales information, all of the transaction data was transformed into a dimensionless index for the analysis to preserve confidential information. Since the sales index and transaction index use different transformations, their values in the models cannot be compared.

We created linear regression models using all the explanatory variables considered in the sales index models. The findings of the transaction models are shown in Figure 31 and Figure 32 in the Appendix. The R^2 for the ten and twenty-four month models were 0.77 and 0.75 respectively. The models used the linear format, and both include interaction variables, similar to the sales models, thus the average effect of daylight on number of transactions for the chain as a whole must be predicted by averaging the combined interaction effects for each store.

Model Name	Net Effect of Daylight	group F-test
Linear 10 months	**+2.1%**	>.005
Linear 24 months	**+1.2%**	>.005

Figure 18: Net Effect of Daylight on Number of Transactions per Store

Figure 18 shows that the chain-wide average net effect of daylight is positive for both models, ranging from a 1% to 2% increase in number of transactions.

The interaction variables are all significant as a group (group F-test) in both models, and so were retained as a group. The magnitude of the predicted increase in transactions is modest, and somewhat less than the prediction for the increase in sales for the comparable linear 10-month model. Thus it is likely that the "daylight effect" is working both to increase the amount of traffic through the stores, as evidenced by the increase in the number of transactions, and also to increase the value of each set of purchases, as evidenced by the relatively greater sales effect than transaction effect.

Somewhat surprisingly, the models maintained an almost identical format as the sales models, with all of the same explanatory variables being retained, with the exception of the demographic variables. In the sales transaction models, the demographic variable *housing* was significant for both the ten month and twelve month models, and the variables for *population growth* and *transportation* were significant in only the ten month model. The inconsistency of the demographic variables once again argues that they are slightly less reliable predictors of sales (or in this case, number of transactions) than the other variables which are consistent across all models. The consistency of daylight in predicting a positive effect based on a different outcome variable once again increases our confidence that it is likely to be a true effect.

We did go through the exercise of isolating the effect of daylight independent of its interaction with size of parking, as we did above with the log sales models, and found a similar pattern; when parking is at or above norm, an increase in the number of useful daylight hours per stores is also associated with an increase in the percentage effect on transactions.

Again, per the discussion in the log sales models, this average effect is not large enough to give 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 (say doubling the number of sites from 73 to 150) may have provided greater certainty in the models' predictions.

7. OTHER STUDY FINDINGS

In addition to the regression analysis of sales and number of transactions per store, which form the core of this research, we also looked at the potential energy impacts of the daylighting system and assessed employee and store manager satisfaction with the daylighting design. We assessed the energy impacts to quantify the rather predictable dollar value of energy savings due to skylights combined with automatic photocontrols, which will reliably occur in addition to any sales impact. We looked at employee and manager satisfaction with the daylighting as a way to try to get insight into the causal mechanisms of any daylighting effect, and also to identify any problems that might be associated with the daylighting systems in the stores.

The analysis of energy impacts were based on both interviews with the corporate management and our own estimates of energy savings based on store characteristics and operation schedules. The energy estimates are not based on monitoring. The assessment of employee and manager satisfaction with the daylighting system was based on interviews with the managers and a formal survey distributed to employees. The following sections present our findings in these two areas, and discuss their relevance to the overall study.

7.1. Energy Impacts

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.

7.1.1. Store and Corporate Energy Impacts

The energy savings achieved by this chain are a result of the use of automatic photocontrols that reduce lighting energy use when there is sufficient daylight available in the stores. Longer hours of useful daylight (above threshold) per day result in greater energy savings.

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 the photocontrol settings and operation. The stores are not necessarily using optimized designs, 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.

7.1.2. Statewide Energy Impacts

Applying skylights with automatic photocontrols to new and remodeled retail buildings in California has a potential to provide considerable energy and power savings in the state. California adds about 84.8 million sf of new commercial space each year, of which 4% is groceries and 16% is other retail[1]. This adds up to 17 million sf of new retail construction per year. In California the vast majority of this retail space is single story construction. We know from other sources that 46% of retail space nation wide uses hung ceilings, while 54% uses exposed ceilings[2]. If we assume that of spaces with hung ceiling 50% of the total area could be realistically skylit, and that of the spaces with exposed ceiling the rate is higher, at 75% of the area, then we estimate that there is 10.8 million sf per year that could potentially include skylighting.

If we apply the energy and dollar savings achieved by the average store described above across the whole state, then the value of this savings would be $2.5 million dollars per year, or 13.2 megawatt-hours per year[3]. After the end of ten years of construction, the value would potentially increase ten fold, to $25 million per year, and 132 megawatt-hours[4].

However, as discussed above, the average store does not have an optimum skylight and photocontrol system. If we applied the “better” design, using current best-practices components, this value could be increased to $5.8 million per year or 41.6 megawatt-hours. At the “best” level, with state-of-the-art components capturing the maximum technical potential, these numbers could increase to $7.1 million per year or 58.4 megawatt-hours per year. Again these values should be multiplied by a factor of 10 to get the value after ten years of construction.

The above calculations assume skylights are added only to new buildings. If a retrofit market for skylights and automatic photocontrols developed, these values would potentially increase by about another 50%.

[1] Brooks, M. 2002 “California Electricity Outlook: Commercial Building Systems” Presentation at PIER Buildings Program HVAC Diagnostics Meeting, Oakland, CA, April 16.

[2] Armstrong Industries, 2002, private communication.

[3] These values are based on SkyCalc® runs, which account for lighting, heating and cooling savings, and combine the net annual value of electricity and gas impacts into a blended kWh value.

[4] It is not possible to translate megawatthours into peak megawatt impacts, since the dynamics of climate and electric peaks greatly complicate the equation. A separate study should be done to understand the potential peak impacts of skylighting systems on state power demand.

7.1.3. Energy Impacts Relative to Daylight Effect on Sales

With each of these steps of daylight system performance improvement, the hours of daylight above threshold also increases. Thus, according to our model of sales performance, the daylight sales effect would also increase. 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.

Thus, for a daylighting design of the current (good) performance, the value of the daylight effect was estimated at 45 times greater than the value of the energy savings, using the conservative estimate of a 1.1% sales effect from the 24-month period.

With a fully optimized energy design, with three times the energy savings, this ratio is still maintained at 19 times. Should the much higher 5.7% sales effect from the 10-month period apply, the predicted value of additional sales is worth more than 100 times any energy savings.

7.2. Employee Assessment of Lighting Quality

Employees in all surveyed stores were asked to fill out a brief survey on their personal assessment of the lighting quality in the store. We used the same lighting quality assessment instrument that we have used in previous surveys for Southern California Edison, based on an instrument originally developed by Dr. Peter Boyce at the Lighting Research Center in Troy, New York. Our survey asked employees to rate their opinion of the store’s current lighting conditions, on a scale of 1 to 7, where 1 is “I strongly disagree” and 7 is “I strongly agree,” or 1 is “much worse than norm” and 7 is “much better than norm, depending on the nature of the question. We received 1128 responses from an average of 18 employees in 62 out of 73 of the stores studied.

We then compared the responses of employees in daylit versus non-daylit stores. For all questions, employees in the daylit stores rated all aspects of lighting quality slightly better than those in the non-daylit stores. The responses to the various questions gave daylit stores higher ratings ranging from 1% to 9%, with an average of 5% fewer reported problems. The overall assessment was that the daylit stores were 8% better lit than non-daylit stores within the chain, and also 8% better lit than all comparable stores. Those answers with 5% or greater percentage difference have more than 90% certainty ($p<0.10$).

The comparison between the two types of stores is summarized in Figure 19 below.

1. Overall, the lighting quality in this store is comfortable.
*Daylit stores rated 5% better than non-daylit stores

2. The lighting helps make the merchandise look appealing.
Daylit stores rated 1% better than non-daylit stores

3. The store is uncomfortably bright.
Daylit stores rated 2% better than non-daylit stores

4. The store is uncomfortably dim.
*Daylit stores rated 8% better than non-daylit stores

5. The light fixtures themselves are too bright.
Daylit stores rated 2% better than non-daylit stores

6. There is too much light in some areas and not enough in others.
*Daylit stores rated 9% better than non-daylit stores

7. The lighting makes it difficult to examine detail closely.
*Daylit stores rated 6% better than non-daylit stores

8. Reflections on the merchandise are sometimes a problem.
*Daylit stores rated 6% better than non-daylit stores

9. Skin tones look unnatural under this lighting.
Daylit stores rated 3% better than non-daylit stores

10. It is difficult to distinguish shades of color under this lighting.
*Daylit stores rated 6% better than non-daylit stores

11. The lights sometimes flicker or hum annoyingly.
Daylit stores rated 4% better than non-daylit stores

12. How does the lighting in this store compare to lighting in similar stores?
*Daylit stores rated 8% better than non-daylit stores

* indicates $p<.10$, statistical certainty greater than 90%

Figure 19: Employee Assessment of Lighting Quality

The biggest specific differences reported between the two store types were that:

Daylit stores overall were less uncomfortably dim (8%)

Daylit stores had fewer problems with uniformity (9%)

When these surveys were taken, the daylit stores tended to have higher illumination levels than the non-daylit stores, and indeed employees reported fewer problems with the stores being "uncomfortably dim".

It is especially interesting that the employees reported that the daylit stores had better uniformity by 9% ("There is too much light in some areas and not enough in others"), even though we measured substantially bigger variation in illumination levels in the daylit stores than in the non-daylit stores (the standard deviation of both horizontal and vertical illumination was four times greater in the daylit stores).

7.3. Manager Assessment of Lighting Quality

During the 24-month period store managers assessed the lighting quality in both the daylit and the non-daylit stores to be equally high (86% and 83% respectively). During the 10-month period, many more (2.5x) managers thought the lighting quality in the daylit stores was good or superior than did managers in non-daylit stores.

Managers were also asked if they thought that the lighting quality in their store had a positive effect on sales. Managers of both daylit and non-daylit stores had generally the same opinions. The big difference was between the 10-month period at one-half power and the 24-month period at full power. During the 24-month period, three times as many managers in the non-daylit stores and twice as many managers in the daylit stores thought that the lighting quality had a positive effect on sales, compared to their answers relative to the 10-month period.

Interestingly, the managers' intuitive attitudes contradict our findings. We found both types of stores had higher sales during the 10-month period, and that the daylit stores always had higher sales than the non-daylit stores. The difference in sales between daylit and non-daylit stores was also greater during the 10-month period.

Mangers were asked if they had any comments to volunteer about the lighting at one-half or full power and about their experiences with the skylights and photocontrols. Fifteen out of 73 managers either commented negatively about the reduced light levels or responded that full light levels were better. Three out of the 73 managers volunteered that they found the one-half light levels superior. Two of those three were in skylit stores. Only two volunteered that they thought the energy savings from running the lights at one-half power was important.

Relative to the skylights, six out of the twenty-four managers in skylit stores made strongly positive comments about the skylights, and only one made a negative comment. When asked about specific problems that had ever occurred in the past (indefinite time period), four reported a skylight had leaked once, and one reported that one skylight had been broken for one day. None reported any problems with criminal break-ins or accidental falls, problems with skylights that are sometimes cited as concerns by building owners who are considering the use of skylights.

It should be noted that store managers tend to be focused on their own stores, so they may not be able to make meaningful comparisons to other stores with different conditions.

Thus, we found that store managers tended to have either a neutral or a positive attitude towards the daylighting system. They did not report problems of any greater magnitude than might be expected of any other building function.

8. CONCLUSIONS AND DISCUSSION

This study represents evidence that a major retailer is experiencing higher sales in daylit stores compared to similar non-daylit stores. In addition to replicating the findings of the previous study, this study added other important dimensions of information:

- Average effect of daylighting on sales for all daylit stores in this chain was variously calculated at 0% to 6%, depending on the type of model and time period considered.
- A dose/response relationship was found, whereby more hours of useful daylight in a store are associated with a greater daylight effect on sales.
- A bound of an empirical daylight effect for this chain was detailed, with a maximum effect found in the most favorable stores of about a 40% increase in sales. This upper bound is consistent with our previous finding.
- Daylight was found to have as much explanatory power in predicting sales (as indicated by the partial R^2) as other more traditional measures of retail potential, such as parking area, number of local competitors, and neighborhood demographics.
- Along with an increase in average monthly sales, the daylit stores were also found to have 1-2% increase in the number of transactions per month.
- No seasonal patterns to this daylight effect were observed.
- The value of the energy savings from the daylighting is far overshadowed by the value of the predicted increase in sales due to daylighting: by the most conservative estimate of at least 19 times, and more likely, under current conditions, by 45-100 times.
- During the California power crises, when almost all retailers in the state were operating their stores at half lighting power, the stores in this chain with daylight were found to benefit dramatically, with an average 5.5% increase in sales relative to the other stores in the chain (which also increased their sales compared to the previous period).
- Employees of the daylit stores reported slightly higher satisfaction with the lighting quality conditions overall than those in the non-daylit stores. Most strikingly, they perceived the daylit stores to have more uniform lighting than the non-daylit stores, even though direct measurements showed the daylight stores to have much greater variation in both horizontal and vertical illuminance levels.
- Store managers did not report any increase in maintenance attributable to the skylights.
- The chain studied was found to be saving about $0.24/sf per year (2003 energy prices) due to use of photocontrols, which could potentially increase up to $0.66/sf per year with an optimized daylighting system.

We were allowed extraordinary access to the store sites and employees, and have had the opportunity to review the methodology, findings and conclusions with the retailer management. Thus, we have high confidence in the validity of source data, and the reasonableness of these findings.

8.1. Comparison with Previous Retail Study

In this study we have attempted to make a much more detailed study of the relationship between daylight and retail sales than the previous study. Two major differences existed between this study and the previous study. First, in the current study, we were able to account for many more explanatory variables, including radius-based census data, marketing conditions and other physical conditions of the stores, with on-site verification of physical conditions at all sites. The second major difference is that in this study we described the daylight variable as a scalar rather than a simple yes/no variable.

The retailer participant for this study had a greater range of daylighting and climatic conditions than the previous study participant, whereas the previous study had implemented a highly standardized store and daylight design. This range of conditions allowed us to create a scalar variable for the presence of daylight, based on the number of hours of daylight above a certain illumination threshold per year. Upon analysis, we also discovered that there were a number of collinear relationships between daylighting hours and other conditions at the stores. In the previous study we did not have the resources to study all the interactions of explanatory variables. In the previous study we had no information about parking, which proved to be highly significant in this study and, of particular importance, to interact with the predicted daylight effect.

We had a smaller study population in this study (73 versus 108 previously) and much greater variation in the physical conditions of the stores. Most notably, there was greater variation in the basic store plan and layout. We did not have sufficient information about the remodeling status of each store to include that variable in our analysis, whereas in the previous study, “Months Since Remodel” had been one of the most powerful predictors of sales.

The previous set of store sites had higher levels of interior horizontal daylight illumination, often measured at 100% to 300% of electric illumination levels. The current study site had lower levels of horizontal daylight illumination, typically measured at 50% to 100% of electric illumination levels during the 24 month period (100% to 200% during the 10-month period).

In the previous study we predicted an average 40% net daylight effect for the chain, with a statistical model that was able to explain about 60% of the variation in the sales data. In this study we predicted much lower values for an average daylight effect on sales, from 0% to 6%, with a statistical model that was able to explain about 75% of the variation in the sales data. However, for individual stores in this study with the most favorable daylighting conditions (longest hours of daylight, ample parking areas) the daylighting effect was predicted to be on the order of 40%.

Given the findings of the statistical models for this chain’s average sales, it is likely that we were near the minimum of a viable study population with only 73 sites, one-third of which were daylit. A 50% increase in study sites would have increased the certainty of our findings. Thus, we would recommend that any future study consider 120 sites a minimum study population, and preferably try to achieve 150 or 200 study sites, of which about ½ should include the variable of interest.

8.1.1. New Analysis Insights

In this study we were able to include a number of additional analysis methodologies. First, we were able to compare two different sales periods, which were distinguished by different illumination levels in the stores. During the period with lower illumination levels, the relative daylight effect increased by 4.5%, even while average sales for all stores in the chain rose.

Since we had monthly data, we looked for seasonal effects for daylighting, and in both a two-dimensional analysis and multivariate analysis, we did not observe any seasonal differences in sales patterns between daylit and non-daylit stores. We did not have sufficiently detailed information that would have enabled us to study time-of-day effects. The implication of the lack of a seasonal effect is that daylight would seem to increase customer loyalty throughout the year, rather than just during peak daylight periods, like summer. Thus, we hypothesize that once a customer has decided that they prefer the retailer's stores (perhaps partially due to the presence of daylight) then they continue to shop at the chain throughout the year instead of competitors' stores. This hypothesis would seem to be consistent with general marketing theory about brand loyalty.

We also interviewed the store managers and found that a small percentage of them strongly believed that daylighting increased sales. A survey of store employees found a significant, but very slight increase in positive attitudes towards the lighting conditions in daylit stores. We were not able to interview shoppers, as we did in the previous study. The evidence from the managers' interviews and employee surveys suggests that subjective evaluation of daylight conditions is positive, but less robust than the statistical evidence of an increase in sales.

Discounting subjective evaluation is consistent with other studies that have shown that, in general, people tend to have little conscious awareness of lighting conditions, and that they are likely to be influenced in their evaluation of lighting conditions by outside forces or their education on the issue.[1] Perhaps the best evidence we have of this phenomenon is the increased discussion of the positive effect of daylighting in schools since the publication of the first PG&E Daylighting in Schools study[2]. When we began that study, finding teachers or administrators commenting on the positive effects of daylight was fairly rare, and required prompting. Now, four years later, when we visit schools for surveys or observations, teachers and administrators frequently volunteer opinions about the positive effects of daylight, even when they have no idea why we are visiting the schools or that we were connected with the earlier study.

8.1.2. Why Daylight Hours is a Better Variable than Daylight Yes/No

The daylight conditions in this chain were far more variable than those in the previous study site. First, they ranged over more climatic conditions, which could influence daylight availability. Secondly, there was a greater range in the store designs, with some stores receiving daylight in only part of their main sales area, and a few stores receiving daylight from vertical windows rather than horizontal skylights.

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[1] N Eklund, P Boyce, SN Simpson, "Lighting and Sustained Performance," Journal of the IESNA, Vol. 29, No 1, Winter 2000, p 116-130.

[2] Heschong Mahone Group, *Daylighting and Student Performance*, PG&E 1999.

Since we had more information about each store, in this study, we were able to test a number of different ways of defining the daylight presence in the stores. In addition to the Daylight indicator variable (yes/no), we tried using indicator variables for Vertical Glazing (yes/no), and Partial Daylight (yes/no). Ultimately, putting all of the stores on a single scalar of daylight hours per year seemed to be the most robust approach, and the most useful in providing design guidance.

The presumption here is that, if the presence of daylight is a positive attribute in a store, then more hours of daylight per year will provide a greater benefit. As discussed earlier, in the skylight design typically used in these stores, hours of daylight per year and intensity of daylight at peak periods are strongly related: i.e. the more intense the daylight at peak periods, the more hours of useful daylight per year. However, this relationship is not necessarily a given. It is possible to design skylighting systems that increase useful daylight during morning and evening hours by increasing the penetration of low angle sunlight, while reducing peak intensities by reducing the transmission of high angle sun. While it is our hypothesis that hours of useful daylight per year, rather than average or peak daylight intensity, will likely be a more useful metric for evaluating daylighting systems, we cannot distinguish between the two in this analysis.

8.2. Possible Mechanisms for a Daylighting Effect on Sales

The results from the employee survey suggest that the differences in visual quality between daylit and non-daylit stores can be observed in subjective surveys, but just barely. Employees' evaluations showed a subtle difference in lighting quality between daylit and non-daylit stores. All of the stores, daylit and non-daylit, were judged to be adequately well lit, and none were judged to have lighting problems. The daylit stores were judged to have slightly fewer problems, and slightly better lighting quality overall. Thus, it would seem that the daylight effect is operating at a different level than conscious perception of the lighting environment. This finding is consistent with the informal surveys done in the previous study, where over 90%of the shoppers had not even noticed when the stores had skylights, and yet judged them to be "cleaner" and "more spacious."

Lighting designers in general tend to agree that illumination conditions operate below the level of conscious awareness. Unless the lighting conditions are actively disabling, either too dark or too glaring, people rarely seem to take conscious note of the lighting conditions, or the source of the light. In the previous study, we suggested a number of possible mechanisms for the daylight effect, and below we will discuss these in light of the current study.

Higher illumination levels is perhaps the most obvious candidate for a causal mechanism, since the pathway between illuminance levels and performance is well understood. Other possible benefits of daylight in stores include improved color rendition, improved lighting quality, greater variability in the store's appearance by time of day and season, greater connection to the outdoors through observation of weather conditions, or improved health and morale of the employees (and possibly shoppers) due to biological effects of daylight. We will discuss each of these possibilities in turn

Higher Illumination Levels: Higher illumination levels are likely to increase the visibility of product details, especially for older customers with weaker eyesight. Higher illumination levels may be responsible for subtle biological effects, as discussed below. Higher illumination levels may also increase the general perception of the attractiveness of the sales space and products, as evidenced in the perceptions of the shoppers discussed above.

Two findings of this study suggest that higher illumination levels may be partially responsible for the daylight effect. First of all, more daylight hours per year was directly associated with greater sales. In skylit stores, more daylight hours per year will also be directly associated with higher average illumination levels—since as daylight illumination levels increase there are more hours per year above the design illumination threshold. Secondly, we found that the relative daylight effect was greater during the 10-month period when the average electric illumination levels were lower for all stores, thus the difference in daytime illumination between daylit and non-daylit stores was greater. During this period, since the electric lighting levels were constant for all stores, the daylit stores tended to have slightly higher horizontal illumination levels during all daylight hours.

Illumination levels in the daylit stores is a dynamic condition. Our measurements were based on hand held illumination readings taken during the late winter months generally between 10 am and 2 pm. We observed daylit stores to average 66% higher horizontal illumination than the non-daylit stores during the February-March mid-day period of our measurements. SkyCalc projections suggest that it would average about 133% higher during the summer months.

Figure 20 compares the SkyCalc estimated average horizontal illuminance during the two time periods, 10-month and 24-month, and during peak daylight conditions (July) and minimum daylight conditions (December) for two average stores in the chain, one daylit (dashed lines) and one not daylit (solid lines). During the 10-month time period, all stores operated their electric lights at about ½ power, so that became the minimum illumination in daylit stores, and the additional daylight contribution always increased illumination levels during the day. During the 24-month period, all stores operated at full power, but daylit stores turned off some of their lights during the daytime when threshold daylight illumination conditions were met.

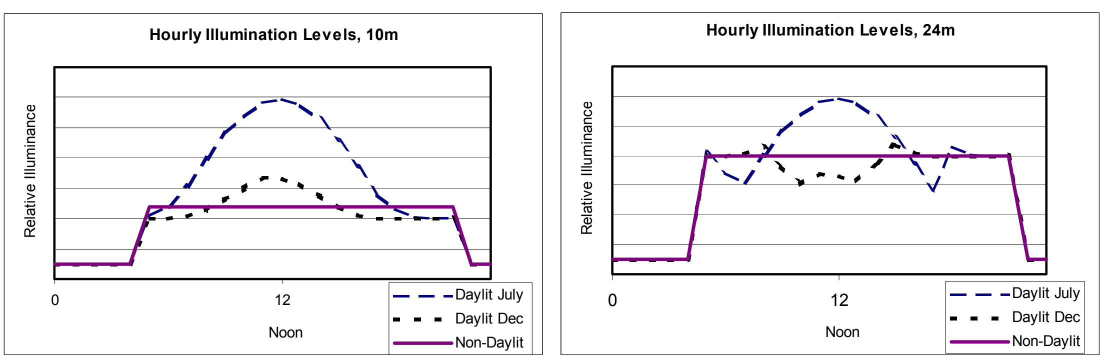

Figure 20: Hourly Illumination Patterns of Average Daylit and Non-Daylit Stores, 10-month (left) and 24-month (right) periods

Based on our understanding of the photocontrol operations controlling the electric lights, and SkyCalc analysis of hourly daylight levels, we believe that during the 24-month period the daylit stores operated above the non-daylit stores' illumination level for about 20% of the store hours. Another 40% of the time, they would have been operating at slightly less than the non-daylit stores' illumination level, and the remaining 40% of the time at the same level. *Thus, increased horizontal illumination may not be solely responsible for the increased sales due to a daylight effect.*

Improved Color Rendition: Daylight has the greatest range of spectral wavelengths of any of our light sources, and is the source our eye has naturally adapted to through millenniums of evolution. With a continuous spectrum of light, all colors will be more vivid and have a more naturally rendered appearance under daylight. Any store which sells products distinguished by color, or where color is a key selection criteria, is likely to benefit from improved color rendition. This particular retailer, as well as the previous study participant, does sell some products that would benefit from better color discrimination. It is possible that there are fewer returns due to poor color selection and greater attraction to products due to more vivid color rendition. In this study, we did not collect evidence on this issue.

Greater Depth Perception: There is a second possible effect of the spectrum of daylight, due to its greater richness in the blue end of the spectrum. One current theory suggests that people perceive a space to be more brightly lit, and that the resulting size of their pupil is smaller, under so-called “scotopic” sources of light, those rich in the blue end of the spectrum. The smaller pupil size is likely to increase the depth of field of the viewer, allowing a shopper to see greater detail over a wider range of focal distances.

Improved Lighting Quality: The daylit stores had consistently higher illumination levels on vertical surfaces. During our daytime observations, average vertical illuminance readings were 62% higher in the daylit stores, and the average minimum readings (average-standard deviation) were 50% higher. The lowest vertical illumination reading found in any daylit store was four times higher than the lowest reading in any non-daylit store.

We examined a set of photographs of a sample of comparable daylit and non-daylit stores looking for obvious changes in appearance or visual quality that we could not capture with our surveyors’ light meter readings. The appearance of the product in the aisles was remarkably similar between the two types of stores. Shadows and highlights on products appeared very similar.

The most obvious differences between the two store types were in the appearance of the floor, ceiling and upper walls. The floor in daylit stores was more likely to have subtle shadows and changes in color, due to alternating patterns of skylight versus electric light dominating the aisles, whereas the floors in the non-daylit stores were very uniform in appearance. Similarly the ceiling in the daylit stores might best be described as “lively,” with daylight bouncing off of many surfaces, compared to a much more uniform appearance of the ceilings of the non-daylit stores. In the non-daylit stores the uniform pattern of bright electric lights tended to accentuate the contrasting darkness of the non-illuminated ceiling. Even when ceilings were the same height, the daylit stores seemed to have higher ceilings since the ceiling surfaces were more brightly lit, attracting the viewer’s eye upwards. The daylit stores also tended to have higher illumination levels on the upper walls and high-mounted signage, creating a bright horizon and perhaps helping with shopper navigation through the store.

Greater Variability: The range of illumination levels in daylit stores is considerably greater than in non-daylit stores, and yet the employees judged the daylit stores to have slightly better lighting quality, and substantially greater lighting uniformity, than the non-daylit stores. The standard deviation for both vertical and horizontal illumination readings was four times greater in the daylit versus the non-daylit stores. While uniformity of illumination is often a key goal of lighting designers, the non-uniformity of the daylit stores may actually be a positive feature.

Daylight variability is a function of both space and time. The variation in illumination levels for daylit stores over time is even greater than the variation in space described above. Highlighted areas move around the store as the sun moves through the day and seasons. A daylit store looks different in the morning than in the afternoon, and different in the summer than in the winter, with slightly changing color of light and patterns of soft shadows. Such variation in appearance may help to stimulate shopper interest over repeated visits, and may also help to keep employees alert and mentally engaged over time.

Connection to the Outdoors: Daylit stores offer some information about the weather outside of a store. Most of the stores in this chain had diffuse skylights that offered no view of the sky, but the intensity of daylight or the passing of clouds is clearly discernable. Rain and hail can be heard through the skylights. This information about weather conditions outside may also have a stimulating effect, as discussed above under “Greater Variability.”

Biological Effects: There is a growing body of research being undertaken to understand the biological effects of light. To date it is clear that bright light exposure during the day helps reinforce the natural circadian rhythms of various hormones and neural transmitters. Bright light, most likely in the natural daylight spectrum favoring blue wavelengths, suppresses melatonin and increases the production of neural transmitters such as serotonin and dopamine. Healthy circadian rhythms have been implicated in better immune function and activity patterns. The illumination intensity, duration, timing and spectral sensitivity of these effects are still being researched, and may likely vary by time of day. We believe these are fairly slow biochemical effects, unlikely to be detectable in less than 30 minutes, and most likely to be reinforced over days of exposure. Thus, short store visits by shoppers are not likely to involve biological effects from daylight exposure. Store employees, on the other hand, may experience some health benefits from working in a daylit environment that reinforces their circadian rhythms. We did not study any indicators that would identify any of these effects. We hypothesize, however, that positive feelings generated from daylight exposure could possibly reinforce general positive feelings towards the store for both shopper and employees.

Although further research will be required to uncover the mechanisms of daylight’s importance, this study reinforces the finding that daylight does truly increase retail sales. We have presented evidence from a second retail sector that daylight can increase retail sales on average for the chain by up to 6%, or for individual stores by up to 40%, depending on the daylight design, parking lot size, and other store variables. The effect of daylighting on sales is of a magnitude similar to more traditional retail location variables and has a value many times greater than the energy savings that accompany daylighting. These results give us greater confidence in recommending daylighting strategies for the design of new retail stores.

9. APPENDICES

9.1. Retail Survey Forms

Attached are three survey forms that were developed for the study, for on-site data collection, to interview the manager, and to survey employees. Any potentially identifying information has been re-coded as option “A,B,C etc”. Some formatting was lost in transferring the forms, but the basic content and structure remains.

9.1.1. On-site Survey Form

RETAIL ON-SITE SURVEY

Store location ______________________ **Store number** ____________

Exterior site information

Location type	urban ❍	strip mall ❍	big-box ❍	rural ❍	other ❍	Comments ____________
Neighborhood	☐ residential		☐ commercial		☐ industrial	
Neighborhood rating	dilapidated ❍ 1	❍ 2	average ❍ 3	❍ 4	high-end ❍ 5	Comments ____________
Building Signage	❍ A	❍ B	❍ C	❍ D	____________	
Main Street Sign	❍ Yes		❍ No			
Main Street Size	Number of lanes ________	Freeway	❍	Boulevard ❍	Secondary ❍	Residential ❍
Main Street Visibility	not visible ❍ 1	very obstructed ❍ 2		some obstructions ❍ 3		few obstructions ❍ 4 / no obstructions ❍ 5
Co-Tenancy	❍ A	❍ B	❍ C	❍ D	❍ E	❍ ____________
Cloud Condition	clear ❍	high thin ❍	puffy ❍	light oc ❍	dark oc ❍	Comments ____________
Sky Condition	stable ❍		changeable ❍			

Photograph

- ☐ Plan with store number — frame #__________
- ☐ Main Street toward store — frame #__________
- ☐ Main Street toward street — frame #__________
- ☐ 100' from entry toward entry — frame #__________

Others: ______________________________

Horizontal Illuminance (in parking lot) ________ fc arrival time: ____________AM/PM

Building manager interview

Permission Granted ❍ Manager ❍ Other

Interview performed ❍ Yes ❍ No **Name** ______________________

Interior building information

Photos

- ☐ 1 frame #__________
- ☐ 2 frame #__________
- ☐ 3 frame #__________
- ☐ 4 frame #__________
- ☐ 5 frame #__________
- ☐ 6 frame #__________
- ☐ 7 frame #__________

Notes

____

____

Illuminance Measurements

Measurement location	Time	Horiz @ 4 feet	L vert @ 2 feet	L vert @ 4 feet	L vert @ 6 feet	R vert @ 2 feet	R vert @ 4 feet	R vert @ 6 feet
Wide aisle u/s								
Wide aisle b/s								
Narrow aisle u/s								
Narrow aisle b/s								
Back aisle u/s								
Back aisle b/s								
Checkout		1	2	3	n/a	n/a	n/a	n/a

Legend: u/s=under skylights or if no skylight exists, b/s = between skylights

Reflectances

- **Floor** ❍ A ❍ B ❍ Other ____________
- **Upper Walls** ❍ A ❍ B ❍ Other ____________
- **Ceiling** ❍ A ❍ B ❍ Other ____________
- **Structure** ❍ A ❍ B ❍ Other ____________
- **Cleanliness** very cln. ❍ 1 clean ❍ 2 normal ❍ 3 dirty ❍ 4 very dirty ❍ 5 Comment____________

Luminaires

- **Verify** ☐ Verify mounting height and spacing with plan survey.
- **Layout** ❍ A ❍ B ❍ C ❍ D ❍ Other ____________
- **Flicker** ❍ Yes ❍ No **Hum** ❍ Yes ❍ No
- **Cleaning** ❍ Clean ❍ Dirty
- **Controls** ❍ A ❍ B ❍ C ❍ D ❍ Other ____________

Skylights ☐ no skylights (if no skylights, ignore the following 5 questions)

- **Type** ❍ A ❍ B ❍ Other____________
- **Well Depth** ❍ A ❍ B ❍ C ❍ D ❍ E ❍ Other____________
- **Cleaning** ❍ Clean ❍ Dirty **Discoloring** ❍ Yes ❍ No
- **Obstructions** ❍ A ❍ B ❍ C ❍ D ❍ Other ________

Thermal Environment

- **Heating** ❍ A ❍ B **Dry bulb temp.** ________ °C or °F
- **Air movement** ❍ A ❍ B **Air velocity** ________ ft/min or m/s
- **Cooling** ❍ A ❍ B **Cycling** ❍ Yes ❍ No

Aural Environment silent quiet normal loud very loud

- **Ambient** ❍ 1 ❍ 2 ❍ 3 ❍ 4 ❍ 5 **Decibels** ________
- **PA** ❍ 1 ❍ 2 ❍ 3 ❍ 4 ❍ 5 **Decibels** ________
- **Air** ❍ 1 ❍ 2 ❍ 3 ❍ 4 ❍ 5 **Decibels** ________
- **Primary Noise Source** ☐HVAC ☐Street ☐Chckout ☐Patrons ☐Other Location________

Olfactory Environment very pleasant neutral very unpleasant

- **Pleasantness** ❍ 1 ❍ 2 ❍ 3 ❍ 4 ❍ 5 Describe____________

Horizontal Illuminance (in parking lot) ________ fc departure time: ____________AM/PM

9.1.2. Manager Interview

Building manager interview (confidential)

Interviewee Name ______________________ **Time**______________________

Title ❍ Manager ❍ Other ______________________

Gender ❍ Male ❍ Female **Eye Glasses** ❍ Yes ❍ No

Age ❍ <30 ❍ 31-40 ❍ 41-50 ❍ 51-60 ❍ > 61

Years at this store ______________ **Years with this company** ______________

1. Have you ever worked at a different store location for this company? ❍ Yes ❍ No

If Yes, location ______________ dates from __________to______________

2. What do you think are this store's major advantages compared with similar stores?

❍ Neighborhood ❍ Visibility ❍ Personnel ❍ Maintenance

Other ______________________

3. Have any new competitors opened up nearby (X distance +/-) in the past three years?

❍ Other ______________________

4. Have any local events in the past three years dramatically affected sales? ❍ Yes ❍ No

❍ Construction ❍ Resurfacing ❍ Flood ❍ Personnel ❍ Crime

❍ Other ______________________

Date(s) ______________ approx. duration ______________

5. On a scale of 1 to 5, how do you rate the electric lighting system in this store?

Part on: ❍ 1 Poor ❍ 2 Fair ❍ 3 Adequate ❍ 4 Good ❍ 5 Superior

All on: ❍ 1 Poor ❍ 2 Fair ❍ 3 Adequate ❍ 4 Good ❍ 5 Superior

Comments ______________________

6. Do you think the electric lighting system in this store impacts sales performance?

Part on: ❍ 1 very negative ❍ 2 negative ❍ 3 no effect ❍ 4 positive ❍ 5 very positive

All on: ❍ 1 very negative ❍ 2 negative ❍ 3 no effect ❍ 4 positive ❍ 5 very positive

Comments ______________________

7. Have you had any problems with the electric lighting system? ❍ Yes ❍ No

❍ frequent burn out ❍ flicker ❍ hum ❍ switching problems

❍ Other ______________________

8. Did this store experience any unexpected loss of power last year? ❍ Yes ❍ No

If Yes, did customers have to leave the store? ❍ Yes ❍ No

Date(s) ______________ approx. duration ______________

Comments ______________________

If there are no skylights, skip the following questions and check here ☐ no skylights

9. On a scale of 1 to 5, how do you rate the light from the skylights in this store?

❍ 1 Poor ❍ 2 Fair ❍ 3 Adequate ❍ 4 Good ❍ 5 Superior

Comments ______________________

10. Do you think the skylights in this store impact sales performance?

❍ 1 very negative ❍ 2 negative ❍ 3 no effect ❍ 4 positive ❍ 5 very positive

Comments ______________________

11. Have you had any problems with the skylights? ❍ Yes ❍ No

☐ Water leaks ☐ Breakage ☐ Crime ☐ Fall-through

☐ Other ______________________

Date(s) ______________ approx. duration ______________

9.1.3. Employee Survey

Store location ____________________________________ **Store number** ________________

LIGHTING QUALITY SURVEY

You are being asked to participate in a voluntary study about the lighting quality in this store. This study is conducted by an independent consultant and your answers are confidential. We ask that you complete this survey and return it to the designated person as soon as possible. If you would prefer, you can mail the form to us directly at "Lighting Survey", 11626 Fair Oaks Blvd. #302, Fair Oaks, CA 95628. *Thank you!*

Do you work full or part time? ❍ full time ❍ part time

Where in the store do you primarily work? ❍ sales floor ❍ back office ❍ other

Please indicate your age. ❍ <30 ❍ 31-40 ❍ 41-50 ❍ 51-60 ❍ > 61

How long have you worked at this store? ________ In years or fraction of a year

Please answer the following questions related to your experience of the lighting in this store as it is today. For each question, please circle the number that most closely matches your opinion, where **1** means you strongly disagree and **7** means you strongly agree.

	strongly disagree	disagree	somewhat disagree	no opinion	somewhat agree	agree	strongly agree
a) Overall, the lighting quality in this store is comfortable.	1	2	3	4	5	6	7
b) The lighting helps make the merchandise look appealing.	1	2	3	4	5	6	7
c) The store is uncomfortably bright.	1	2	3	4	5	6	7
d) The store is uncomfortably dim.	1	2	3	4	5	6	7
e) The light fixtures themselves are too bright.	1	2	3	4	5	6	7
f) There is too much light in some areas and not enough in others.	1	2	3	4	5	6	7
g) The lighting makes it difficult to examine detail closely.	1	2	3	4	5	6	7
h) Reflections on the merchandise are sometimes a problem.	1	2	3	4	5	6	7
i) Skin tones look unnatural under this lighting.	1	2	3	4	5	6	7
j) It is difficult to distinguish shades of color under this lighting.	1	2	3	4	5	6	7
k) The lights sometimes flicker or hum annoyingly.	1	2	3	4	5	6	7

For question 12, please circle the number that most closely matches your opinion of the lighting in this store compared to other stores with which you are familiar.

	worse			the same			better
l) How does the lighting in this store compare to lighting in similar stores?	1	2	3	4	5	6	7

Retail Sales Model Results

9.1.4. Natural log Models

Summary Stats for Natural Log Models						
Variable Description	**Variable**	**Min**	**Max**	**Range**	**Ave**	**SD**
ln(sales index 24m)	LogSales10m	7.09	8.56	1.48	7.78	0.32
ln(sales index 10m)	LogSales24m	6.97	8.53	1.56	7.72	0.36
ln(Total Area)	logArea	1.00	1.06	0.06	1.04	0.01
Longer work week, yes/no	Hours	0.00	1.00	1.00	0.36	0.48
ln(Age)	logAge	1.00	3.68	2.68	2.11	0.59
Percent Population Growth, 2000-1990	PopGrow	1.00	13.18	12.18	5.09	2.55
Number of sister stores within certain radius	Co-mktg	1.00	5.00	4.00	3.93	1.26
Number of competitor stores within radius 1	Compet 1	0.00	10.00	10.00	2.40	2.22
Storefront height scalar	Height	1.00	3.57	2.57	1.91	0.47
ln(Parking)	logPark	1.00	1.29	0.29	1.17	0.07
Outlier Store	Out44					
Daylit hours per year greater than threshold	DayHrs	270.00	1800.32	1530.32	1090.55	408.86
Parking * DayHrs	ParkDH	447.95	4557.73	4109.77	2654.69	1289.44

Figure 21: Summary Statistics for Natural Log Models

These are only the variables found significant in the Log Models. For more information on other variables considered, look at the Descriptive Statistics table for the Linear Models, also included in the Appendix. For all models, we have dropped out the intercept values for the model equations, since they do not effect any results, and they became difficult to keep consistent across the transformed linear and log models.

Model Name: LN 10m					
Variable Description	**Variable**	**B**	**Std. Error**	**t**	**Sig.**
ln(Total Area)	logArea	0.59	0.18	3.26	0.002
ln(Age)	logAge	0.28	0.05	6.10	0.000
Transportation variable, 1990	Transport	0.00	0.00	-2.53	0.014
Education variable 1990	Education	0.00	0.00	2.87	0.006
Number of sister stores within certain radius	Co-mktg	0.07	0.02	3.38	0.001
Number of competitor stores within radius 1	Compet 1	-0.05	0.02	-2.81	0.007
Storefront height scalar	Height	-0.01	0.00	-2.27	0.027
ln(Parking)	logPark	-0.41	0.08	-4.94	0.000
Outlier Store	out440	0.68	0.18	3.84	0.000
Daylit hours per year greater than threshold	DayHrs	0.00	0.00	-2.50	0.015
Age * DayHrs	AgeDH	0.00	0.00	-1.71	0.092
Parking * DayHrs	ParkDH	0.00	0.00	3.63	0.001

Model Summary:	
RMSE	0.17
R^2	75.7%

Figure 22: Log Model of 10-Month Sales, 2001

Model Name: LN 99, 01					
Variable Description	**Variable**	**B**	**Std. Error**	**t**	**Sig.**
ln(Total Area)	logArea	7.694	2.08	3.69	0.001
ln(Age)	logAge	0.246	0.05	5.19	0.000
Transportation variable, 1990	Transport	-0.00002	0.00	-3.84	0.000
Education variable 1990	Education	0.00001	0.00	3.68	0.001
Number of sister stores within certain radius	Co-mktg	0.091	0.02	3.85	0.000
Number of competitor stores within radius 1	Compet 1	-0.056	0.02	-2.97	0.004
Storefront height scalar	Height	-0.161	0.07	-2.34	0.023
ln(Parking)	logPark	-1.823	0.41	-4.41	0.000
Outlier Store	out440	0.651	0.20	3.27	0.002
Daylit hours per year greater than threshold	DayHrs	-0.001	0.00	-3.06	0.003
Parking * DayHrs	ParkDH	0.00024	0.00	3.20	0.002

Model Summary:	
RMSE	0.19
R^2	74.7%

Figure 23: Log Model of 24-Month Sales, 1999-2000

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 24: Order of Entry and Partial R^2, Log 10 Month Sales, 2001

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

Figure 25: Order of Entry and Partial R^2, Log 24 Month Sales, 1999-2000

9.1.5. Linear Models

Summary Stats for Linear Models (all variables considered)						
Variable Description	**Variable Name**	**MIN**	**MAX**	**RANGE**	**MEAN**	**STD**
OUTCOME (DEPENDANT) VARIABLES						
Sales index per store, 24 mo avg for 1999-2000	Sales24	1068.40	5068.17	3999.77	2390.61	867.77
Sales index per store, 10 mo avg for 2001	Sales10	1195.07	5234.18	4039.11	2515.70	828.65
EXPLANATORY (INDEPENDANT) VARIABLES						
CORPORATE VARIABLES						
Total Sales Area Scalar	Area	1.00	1.87	0.87	1.50	0.19
Longer work week, yes/no	Hours	0.00	1.00	1.00	0.36	0.48
Store Age Scalar, relative age from date of first opening	Age	1.00	19.00	18.00	4.17	3.03
Manager seniority scalar	Mgr	1.00	56.00	55.00	21.64	13.65
CENSUS VARIABLES						
Housing Status	Housing	2182.00	45229.00	43047.00	22983.55	11123.58
Population Density, 2000	Pop	6701.00	321692.00	314991.00	86522.51	60056.14
Percent Population Growth, 2000-1990	PopGrow	1.00	13.18	12.18	5.09	2.55
Ethnic Status, 2000	Ethnic	0.29	0.92	0.64	0.63	0.15
Households, 2000	Household	4026.00	175163.00	171137.00	44657.60	32533.27
Income 1990	Income	10813.34	29831.75	19018.41	17537.69	4711.22
Economic Status 1990	Econ	0.02	0.23	0.21	0.10	0.05
Education variable 1990	Education	2886.00	143727.00	140841.00	42678.78	31059.53
Language variable, 1990	Language	44.00	97023.00	96979.00	8873.19	15428.92
Transportation variable, 1990	Transport	286.00	36884.00	36598.00	7879.32	6884.83
LOCAL MARKET INFLUENCES						
Number of sister stores within certain radius	Co-mktg	1.00	5.00	4.00	3.93	1.26
Number of competitor stores within radius 1	Compet 1	0.00	5.00	5.00	1.44	1.29
Number of competitor stores within radius 2	Compet 2	0.00	10.00	10.00	2.40	2.22
Co-tenant scalar	Cotenant	0.00	4.00	4.00	1.49	1.39
Number of lanes on the main street	Lanes	2.00	8.00	6.00	4.55	1.32
Street visibility scalar	Visible	1.00	5.00	4.00	3.30	1.14
Building signage is "typical" yes/no	Sign	0.00	1.00	1.00	0.90	0.30
Flag for negative sales event in neighborhood	Event	0.00	1.00	1.00	0.25	0.43
Storefront length scalar	Length	1.00	3.79	2.79	1.97	0.57
Storefront height scalar	Height	1.00	3.57	2.57	1.91	0.47
Parking scalar	Parking	1.00	3.63	2.63	2.22	0.64
STORE COMFORT CONDITIONS						
Daylit hours per year greater than threshold	DayHrs	270.00	1800.32	1530.32	1090.55	408.86
Average of all vertical illuminace readings, scalar	VertAve	2.21	31.83	29.62	6.93	4.02
Standard Deviation of vertical illuminace scalar	VertSD	1.00	41.13	40.13	2.99	4.67
Atypical luminaire layout yes/no	Luminaire	0.00	1.00	1.00	0.12	0.33
Electric lighting percent on, scalar	Lightson	1.00	4.00	3.00	2.44	0.78
Ceiling height scalar	ClgHt	1.00	2.50	1.50	1.50	0.32
Noticeable air movement ,yes/no	Air	0.00	1.00	1.00	0.10	0.30
Odor scalar	Smell	2.00	5.00	3.00	3.04	0.48
Noise scalar	Noise	3.00	8.00	5.00	5.19	1.24
INTERACTION VARIABLES (all based on scalars above)						
Sales Area * DayHrs	AreaDH	1.00	6.92	5.92	4.66	1.76
Age * DayHrs	AgeDH	1.00	17.79	16.79	5.73	4.13
Longer Hours * DayHrs	HoursDH	1.00	3.83	2.83	2.71	1.19
PopGrowth * DayHrs	PopGrowDH	1.00	13.18	12.18	5.09	2.55
No. sister stores * DayHrs	MktgDH	1.00	16.67	15.67	7.88	3.69
No. Competitors w/in Radius 1 * DayHrs	Comp1DH	1.00	21.27	20.27	6.96	5.19
Frontage height * DayHrs	HeightDH	1.00	8.38	7.38	4.70	2.10
Parking * DayHrs	ParkDH	1.00	10.17	9.17	5.93	2.88
Area*DayHrs*Hours	AreaDHhours	1.00	4.03	3.03	2.79	1.25

Figure 26: Summary Statistics for All Variables Considered in Linear Models

Model Name: Linear 01					
Variable Description	**Variable**	**B**	**Std. Error**	**t**	**Sig.**
Total Sales Area Scalar	Area	1051.87	327.90	3.21	0.002
Store Age Scalar, relative age from date of first openin	Age	146.97	24.53	5.99	0.000
Transportation variable, 1990	Transport	-0.04	0.01	-2.67	0.010
Education variable 1990	Education	0.01	0.00	2.78	0.007
Number of sister stores within certain radius	Co-mktg	180.89	52.71	3.43	0.001
Number of competitor stores within radius 1	Compet 1	-122.49	42.79	-2.86	0.006
Storefront height scalar	Height	-416.25	150.17	-2.77	0.007
Parking scalar	Parking	-579.25	105.31	-5.50	0.000
Outlier Store	Out44	2183.45	449.62	4.86	0.000
Daylit hours per year greater than threshold	**DayHrs50**	-1.41	0.43	-3.25	0.002
Age * DayHrs	AgeDH	-0.08	0.05	-1.73	0.089
Parking * DayHrs	ParkDH	0.73	0.18	4.22	0.000

Model Summary:	
RMSE	439.95
R^2	76.5%

Figure 27: Linear Model of 10 Month Sales, 2001

Model Name: Linear 99-00					
Variable Description	**Variable**	**B**	**Std. Error**	**t**	**Sig.**
Total Sales Area Scalar	Area	1305.09	340.88	3.84	0.000
Store Age Scalar, relative age from date of first o	Age	110.68	22.56	4.91	0.000
Transportation variable, 1990	Transport	-0.06	0.02	-4.14	0.000
Education variable 1990	Education	0.01	0.00	3.95	0.000
Number of sister stores within certain radius	Co-mktg	217.31	56.38	3.85	0.000
Number of competitor stores within radius 1	Compet 1	-129.86	45.18	-2.87	0.006
Storefront height scalar	Height	-388.92	161.60	-2.41	0.019
Parking scalar	Parking	-516.95	111.11	-5.61	0.000
Outlier Store	Out44	1981.51	484.82	4.09	0.000
Daylit hours per year greater than threshold	**DayHrs**	**-1.57**	**0.45**	**-3.47**	**0.001**
Parking * DayHrs	ParkDH	0.64	0.18	3.47	0.001

Model Summary:	
RMSE	474.65
R^2	75.3%

Figure 28: Linear Model of 24 Month Sales, 1999-2000

Model Name: Linear 01			
Variable Description	**Variable**	**Order of Entry**	**Partial r^2**
Total Sales Area Scalar	Area	4	0.054
Store Age Scalar, relative age from dat	Age	1	0.318
Transportation variable, 1990	Transport	12	0.028
Education variable 1990	Education	11	0.006
Number of sister stores within certain r	Co-mktg	6	0.034
Number of competitor stores within ra	Compet 1	5	0.029
Storefront height scalar	Height	7	0.035
Parking scalar	Parking	3	0.079
Outlier Store	out440	2	0.104
Daylit hours per year greater than t	**DayHrs50**	**9**	**0.053**
Age * DayHrs	AgeDH	10	0.017
Parking * DayHrs	ParkDH	8	0.008

Figure 29: Order of Entry and Partial R^2, Linear 10 Month Sales, 2001

Model Name: Linear 99-00			
Variable Description	**Variable**	**Order of Entry**	**Partial r^2**
Total Sales Area Scalar	Area	4	0.056
Store Age Scalar, relative age from date of first op	Age	1	0.276
Transportation variable, 1990	Transport	8	0.016
Education variable 1990	Education	9	0.060
Number of sister stores within certain radius	Co-mktg	6	0.033
Number of competitor stores within radius 1	Compet 1	5	0.044
Storefront height scalar	Height	7	0.052
Parking scalar	Parking	3	0.070
Outlier Store	Out44	2	0.088
Daylit hours per year greater than threshold	**DayHrs50**	**11**	**0.050**
Parking * DayHrs	ParkDH	10	0.001

Figure 30: Order of Entry and Partial R^2, Linear 24 Month Sales, 1999-2000

9.1.6. Linear Transaction Models

Summary statistics for the transaction index models are the same as the linear sales index models, and are presented earlier in Figure 26.

Model Name: Linear Transactions 2001					
Variable Description	**Variable**	**B**	**Std. Error**	**t**	**Sig.**
Total Sales Area Scalar	Area	16.23	6.49	2.79	0.007
Store Age Scalar, relative age from date of first o	Age	2.68	0.48	5.60	0.000
Housing variable, 2000	Housing	0.0004	0.00	3.37	0.001
Number of sister stores within certain radius	Co-mktg	2.80	1.05	2.65	0.010
Number of competitor stores within radius 1	Compet 1	-3.87	0.83	-4.65	0.000
Storefront height scalar	Height	-9.35	2.80	-3.34	0.001
Parking scalar	Parking	-11.77	2.04	-5.77	0.000
Outlier Store	Out44	36.92	8.75	4.22	0.000
Daylit hours per year greater than threshold	DayHrs50	-0.0255	0.01	-3.07	0.003
Age * DayHrs	AgeDH	-0.0018	0.00	-1.96	0.054
Parking * DayHrs	ParkDH	0.0131	0.00	3.95	0.000

Model Summary:	
RMSE	8.44
R^2	77.2%

Figure 31: Linear Model of 10 Month Transactions, 2001

Model Name: Linear Transactions 9900					
Variable Description	**Variable**	**B**	**Std. Error**	**t**	**Sig.**
Total Sales Area Scalar	Area	16.23	6.49	2.66	0.010
Store Age Scalar, relative age from date of first o	Age	2.51	0.46	5.48	0.000
Transportation variable, 1990	Transport	-0.0008	0.00	-2.98	0.004
Percent Population Growth, 2000-1990	PopGrow	-16.5897	5.86	-2.83	0.006
Housing variable, 2000	Housing	0.0005	0.00	3.08	0.003
Number of sister stores within certain radius	Co-mktg	3.61	1.16	3.10	0.003
Number of competitor stores within radius 1	Compet 1	-3.95	0.91	-4.33	0.000
Storefront height scalar	Height	-7.40	3.31	-2.24	0.029
Parking scalar	Parking	-10.87	2.24	-4.84	0.000
Outlier Store	Out44	25.76	10.23	2.52	0.015
Daylit hours per year greater than threshold	**DayHrs**	**-0.04**	**0.01**	**-3.88**	**0.000**
Parking * DayHrs	ParkDH	0.01	0.000	3.87	0.000

Model Summary:	
RMSE	9.51
R^2	75.2%

Figure 32: Linear Model of 24 Month Transactions, 1999-2000

9.2. Parking Area Verification Process

During the course of analysis it was discovered that some of the parking lot counts collected in the initial plan review phase of data collection did not seem plausible. Many of the site plans reviewed were old or incomplete, and it was possible that the parking lot had been modified since the plan date. Since the parking lot variable was quite significant in initial models of sales performance, we decided to verify the parking lot counts during the study period.

We obtained parking lot counts from the retailer for about 80% of the store sites. However, these counts were of uncertain dates and based on a variety of counting methodologies. We also obtained low-resolution aerial photographs for about 80% of the sites (not the same 80%), from which we could estimate the parking capacity of the lots. While the aerial photos were considered the most reliable in terms of time period (they were all from approximately the study period) they were often difficult to interpret.

We followed the following methodology to finalized the parking data:

1) We first compared the retailer provided counts to our initial counts.
2) If the two counts were within 15% of each other, we assumed our count to be accurate, since it was based on a consistent counting methodology.
3) If the counts varied by more than 15%, we proceeded to examine the aerial photographs to see if we could determine which count was (more) correct. Using the aerial photograph counts, we also attempted to validate any one of three possible methodologies that might have been used to generate the retailer counts. From this exercise, it was determined that:
    a) The retailer counts did not use a consistent counting methodology, as we had been warned
    b) There was not a clear trend between the retailer or HMG counts being more accurate or consistent
    c) We also compared aerial counts to a few stores where we could verify the actual parking counts with site visits. In these cases, we found the aerial counts to be within 5-15% of the actual counts.
4) Therefore, if the aerial and one of the other counts were within 15% of each other, we accepted either the retail or HMG count that was closest to the aerial count.
5) If neither the retail or HMG count were within 15% of the aerial count, we accepted the aerial count.
6) There were a few cases where we could not validate the HMG counts via this method (because not all three sources were available), in which case we accepted the HMG count.

9.3. Statistical Terminology

The following briefly describes key statistical terms in the report.

Term	Name	Definition
R	Correlation Coefficient *Or* Pearson correlation	Measures the strength of the linear relationship between two variables It can take on the values from -1.0 to 1.0, where -1.0 is a perfect negative (inverse) correlation, 0.0 is no correlation, and 1.0 is a perfect positive correlation.
p	p-value *Or* significance *Or* Sig.	A p-value is a measure of the certainty you have that a relationship exists between an explanatory variable (e.g., smoking) and an outcome variable (e.g., cancer). It is a measure of how much evidence you have that the null hypothesis – that no relationship exists – is not true. The p-value is the probability that you are *falsely* rejecting the null hypothesis, i.e., that you are *falsely* declaring that a relationship exists (e.g., between smoking and cancer.) The smaller the p-value, the more evidence you have. The probability of a false rejection of the null hypothesis in a statistical test is called the significance level. A p-value can vary from >.00 to <1.0. The significance level is 1-p, expressed as a percentage. So if a p-value is .01, the significance level is 99%. Typically, in statistical tests, one sets a threshold for an acceptable significance level. In such a case, if the p-value is less than some threshold (usually .05, sometimes a bit larger like 0.1 or a bit smaller like .01) then you reject the null hypothesis, and conclude that there is a reasonable likelihood of a relationship between the explanatory variable and the outcome.
F-Test		A statistical hypothesis test based on the F distribution where the null hypothesis is that a set of B coefficients are simultaneously zero. The alternative hypothesis is that there is at least one B coefficient in the set that is not zero.

Figure 33: Glossary of Statistical Terminology

Term	Name	Definition
R^2	Regression correlation coefficient	A value between 0 – 1.0 that indicates how well an X value (or the independent or explanatory variables in the regression) explains a Y value (the dependent variable). Technically, the regression equation is: $Y= B_0+B_1X_1+ B_2X_2+…+ B_nX_n+e$ where B_0= intercept, e=error, so as Xs change, Y, the dependent variable, also changes., and variations in X values cause variations in Y. R^2 is defined as the percentage of total variation in Y explained by the independent variables. If R^2 is equal to 1, then entire variation in Y is explained by the independent variables, i.e. the model is very good, and the X variables have perfect explanatory power (for explaining Y). So, the higher the value of R^2, the better the model is for that set of data. Models explaining data that have a high degree of inherent variation, such as individual behavior, will have a much lower R^2 than models explaining more predictable events, such as group averages.
B	B Coefficient	Technically, the regression equation is: $Y= B_0+B_1X_1+ B_2X_2+…+ B_nX_n+e$ where B_0 is the intercept (constant), and B_1 ,B_2 ,…,B_n are the slopes of the regression equation, or the coefficients of the Xs, (or the independent variables), and e is error. A particular B_i (i=1,2,…,n) shows how a particular X_i variable is related to Y. If a B_i coefficient is a positive number, an increase in X_i by one unit increases Y by the amount of the B_i coefficient.
df	Degrees of Freedom	The total number of observations minus the number of restrictions on the observations. For a regression model, the degrees of freedom is equal to the (number of observations - one) – (number of explanatory variables in the model). For example, the log models in this report consist of (73-1)-(11) = 72-11=61 degrees of freedom.