"FOR GOOD DESIGN, YOU PAY NOW.
FOR BAD DESIGN, YOU PAY LATER."- OR DO YOU?

by

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in partial fulfillment of the requirements for the degree of

Master of Science in Real Estate Development

at the

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ABSTRACT

What is the value of architectural design on office building income? This empirical study of 296 office building located in 11 Metropolitan Statistical Areas (MSA) hopes to quantitatively determine if a plain vanilla cereal box suburban office building commands more or less net operating income than an office building with a higher level of design.

Previous empirical studies have found a strong influence of design on rents but were limited in geography, building characteristics and total number of observations. In an important study by Vandell and Lane (1990), they found that good architecture commanded a premium of over 20% in office rents. Also, their study showed that good design cost more to produce on average, but not necessarily in every case.

Data was gathered from a portfolio of US office buildings and consisted of building metrics and property level 2000-2005 Net Operating Income (NOI). This base data set, MSA dummy variables and architectural attribute dummy variables (created by the authors) formed the backbone of the research. Multiple log linear regression analysis was conducted to identify the economic effects of good design.

In addition, a survey taken by 31 architects was used to capture subjective rankings on the all 296 office buildings to determine if there is a consensus as to what constitutes good design. It is hoped that these professionals, who are formally trained and are practicing in the field, are well-qualified to evaluate the design of each building.

The survey results showed that the architects' responses are idiosyncratic and subjective. Not only did the individual participant's rankings show no significant relationship with one another, but also did not exhibit any relationship with actual building NOI.

The empirical study found that the market paid a premium of 7.9% for buildings with non-center cores. Also, a significant 11.7-13.2% premium was paid for properties with non-rectangular and non-square shaped floor plans. Finally, buildings with 60% to 90% exterior windows commanded a substantial 10.7% premium. These results imply that better-designed buildings generate higher NOI either because the tenants are willing to pay a premium or because the operating costs of the building are less, or both.

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CHAPTER I: INTRODUCTION

The research was born from a single question that has been asked by real estate developers as well as architects – how much does "good" design pay? Or in other words, what is the relationship between the economic value of design and a building's ability to generate income from the market? Does a plain vanilla cereal box office building generate more or less income than a well designed office building?

Though real estate professionals and architects believe that good design generates higher building income, there is only a small body of research conducted to accurately measure the link between design and building income. One of the main difficulties is to accurately measure "good" design since design is temporal, regional and highly subjective. Without consistent metrics to evaluate good design, it is very difficult to isolate design from location, prevalent market conditions, occupancy and the like. Therefore, one of the most basic concerns facing developers/architects/tenants is to identify what constitutes "good" design[1]. Are there consistent design attributes which architects, developers and tenants agree are beneficial for all? If there are, then how much does each design attribute contribute to the overall building income?

Objectives and scope of research

Utilizing actual property level Net Operating Income (NOI) gathered from a large portfolio of US office properties from 2000-2005, this research investigates the correlations be-

[1] Within the scope of this research, "design" refers to the design of the office building

tween NOI and design characteristic of 296 US office properties. In other words, the research investigates whether the market pays a premium for good design or not.

The research also attempts to evaluate "good" design using two inputs -

i. Subjective ranking of exterior design quality of each property by architects

ii. Objective measurement of specific physical characteristics of each property

The research hopes to discover relationships between design and NOI as well as any correlations between the subjective rankings and objective characteristics. As architects who have participated in the design and construction of the built environment, the authors hope that this research will aid professionals in determining how much design contributes to the value of an office property.

In earlier studies, office building rents are used to empirically evaluate the economic value of good design. This study deviates from using rents and utilizes NOI, which is a more complete metric (when compared to rent) as it captures rent and vacancy effects as well as operating expense effects. Therefore, the question of whether "good" design pays, in this study, refers to the investor/developers/owner's concern as to how much income is generated by "good" design.

Summary of findings

The results of the subjective measure of design are as follows:

i. The Architect's subjective survey scores bear little relationship to the objective measures of good design (floor plate category, building core location and window percentage). Not only are 75% of these variables statistically insignificant, the remaining statistically significant variables are often of opposite signs.

ii. Since the Survey respondents' responses have low correlations, it can be safely stated that the individual responses are idiosyncratic. Consequently, among our survey sample of young architects, there is little consensus in terms of "good" design.

The results of the objective measures of design are as follows:

i. Properties that are located within high daytime employment areas enjoy higher average NOI per SF

ii. Properties with a Class A designation enjoy an 8.5% increase in NOI per SF in comparison to Class B or C designated properties.

iii. As a building's total rentable square footage (SF) increases, its ability to command higher average NOI per SF increases.

iv. Buildings with non-center cores produce a 7.9% premium versus buildings with centrally located cores.

v. With respect to buildings having a rectangular floor plan, buildings with either non-square/non-rectangular or curved floor plans command an 11.7-13.2% premium in average NOI per SF.

vi. With respect to buildings having 30-59% exterior windows, buildings with 60-89% exterior windows exhibit a 10.2% premium in average NOI per SF.

vii. There is little relationship between the subjective scores of architects and the average NOI per SF generated from 2000-2005.

CHAPTER II: WHAT IS GOOD DESIGN?

There is substantial discussion within the architectural community as well as in the real estate community regarding the importance of good design. A number of issues ranging from spatial form (Brown, M Gordon[2], 1999) to role of design in real estate valuation (Nourse and Roulac[3], 1993) to design and social malaise (Coleman[4], 1985) as well as design and corporate identity (Olins[5], 1990) have been previously explored.

Since the late 1970's, there has been a growing body of research focusing on the issue of design within office properties. Several studies have identified building characteristics that positively influence property value or rents. Brennan et al.[6] (1984), whose study of Chicago's Central Business District (CBD) discovered that the vertical height of a building has a strong effect on the rental function. In separate studies conducted by Mills[7] (1992) and Shilton and Zaccaria[8] (1994) observed that height as well as the floor area / size of the office buildings have a strong impact on the value of the property.

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[2] *Design and value: Spatial form and the economic failure of a mall* – The Journal of Real Estate Research, 1999 by Brown, M Gordon

[3] *Linking Real Estate Decisions to Corporate Strategy* - The Journal of Real Estate Research, 1993 by Nourse, Hugh O. and Roulac, Stephen E.

[4] *Utopia on trial: Vision and reality in planned housing* (London: Hilary Shipman, 1985.) by Coleman, Alice.

[5] *Corporate Identity: Making Business Strategy Visible Through Design.* (Cambridge, Massachusetts: Harvard Business School Press, 1989.) by Olins, Wally

[6] *Office Rent in the Chicago CBD.* Journal of the Real Estate Economics, 1984 by Brennan, T. P., R. E. Cannady, and P. F. Colwell

[7] *Office Rents Determinants in the Chicago Area* – Journal of Real Estate Economics, 1992 by Mills, E.S.

[8] *The Avenue Effect, Landmark Externalities, and Cubic Transformations: Manhattan Office Space* - Journal of Real Estate Finance and Economics, 1994 by Shilton. L and A. Zaccaria

Hough and Kratz[9] (1983) tested a large set of building characteristics and determined that building age, number of floors and architectural character were significant determinants of average rent per square foot for the office buildings in Chicago, Il.

What is "good" design? How is it defined?

Although there is significant research on the impact of design on property value or rent, there is very little literature on the definition of "good" design in terms of measurable factors/characteristics. In a presentation made by Morrell[10] (1994), he outlined the key features of a well designed building, which include functionality ("fitness for purpose and benefit to end users"), aesthetics ("order, expression, integrity, detail"), sensitivity to place, flexibility, durability, sustainability, efficiency and value. Morrell recommended design quality valuation through three main components of design – "build quality", "functionality" and "impact". The "build quality" included construction type, building performance as well as the engineering systems. "Functionality" included the building use, space and access. The "impact" component included the urban and social integration, internal environment, building form and materials, and character and innovations. While the "build quality" and, to a large extent, "functionality" can be captured or evaluated through performance measures, the third component – "impact"- is the most difficult to isolate.

Hough and Kratz (1983) identified "architecturally significant" properties as those that were award-winning or officially recognized by authorities as landmarks. However, there

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[9] *Can 'Good' Architecture Meet the Market Test?* Journal of Urban Economics, 1983 by Hough, D. E., and C. G. Kratz

[10] "Paul Morrell is a commissioner at Commission for Architecture and the Built Environment (CABE). He has a particular interest in measuring the value to clients of good architecture and design." – RIBA (Source: http://www.architecture.com/go/Architecture/Events_3324.html)

is insufficient definition of what constitutes good design or good architecture, except as identified by an architectural jury or authority[11].

In another important study on this topic, Vandell and Lane[12] (1989) define "design" to include "aesthetics" but not the functional aspects of building. They have assumed that - "…the design amenity provides 'aesthetic' utility in the sense that the user (or observer) derives pleasure from the visual environment created by the structure. This benefit is considered separate from the 'functional' utility which directly facilitates the activities housed by the structure." The study has limited its definition of "good" design to external building appearance and public interior spaces.

There is a body of research on the functional as well as the building quality components which identify aspects/characteristics of a well-designed office building. Several design books[13] outline that good office buildings would be a) flexible and technologically-advanced working environments, b) secure settings with good building engineering systems, c) durable and accessible, d) and aesthetically-pleasing.

Design of office buildings need to address the needs of both the office users as well as the visitors and requires careful considerations of how the office spaces and public spaces are detailed and finished. Also, well-maintained employee and visitor support spaces like the

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[11] The authors acknowledge that an in-depth examination of architectural competitions and jury award criteria may bring to light key considerations for what constitutes "good" or "excellent" design as perceived by the architectural community. This is outside the scope of this research and will be limited to the literature review on the topic.

[12] *The economics of architecture and urban design: some preliminary findings* Journal of Real Estate Economics, Volume 12 (2.12), page 239, 1989 by Vandell, K. and Lane, J

[13] *Tower and office: from modernist theory to contemporary practice* by Iñaki Ábalos & Juan Herreros; *The art of office buildings: Sullivan's Wainwright & the St. Louis real estate boom* by John D. Randall; *Office building design* edited

convenience store, lobby, atrium, cafeteria, toilets, and fitness areas increase a building quality as do the operation and maintenance areas such as kitchens, IT closets and loading docks. Other key recommendations for successful office buildings are cost-effective high performance building operations and maintenance systems. Additionally, well-integrated responses to tenant requirements like degree of public access, operating hours, flexibility in floor plan configuration to accommodate growth demands, electronic equipment and technology requirements, acoustical requirements, special floor loading and filing/storage requirements, special utility services, any material handling or operational process flows play a crucial role in the design of a "good" office building.

It is widely accepted that employee productivity increases if their office is located in a building with access to windows, views and the ability to control one's immediate environment. Adequate natural lighting is recognized to improve the health and psychological comfort of office workers. In addition to light, special considerations are recommended to reduce internal[14] as well as external[15] noise pollution in the work environment.

What are the Subjective measures of good design?

To measure the subjective design quality of each property, 31 architects completed a web based survey and ranked 296 office buildings' design on a scale of 1-10.[16] The scores from these professionals, who have been formally trained and have practiced in the field of architecture, generated the numerical ranking of each building in terms of "good" design, as

by Mildred F. Schmertz; *New office design* by Otto Riewoldt; *The new office: designs for corporations, people & technology* by Karin Tetlow

[14] From surrounding occupants, mechanical systems, etc

[15] Due to proximity to busy streets, highways, etc

[16] Additional information on the architect's score will be discussed in chapter V

perceived by these architects. Instead of attempting to create an objective measure of subjective design attribute(s), a conscious effort was made to draw on the professional expertise of the survey participants and have them identify, through a numerical ranking system, buildings that are well- or poorly designed. Within the confines of this data set, a building is considered "well-designed" if its score is above survey average and conversely, a building is considered "poorly-designed" if it's ranking is significantly below the survey average.

What are the Objective measures of good design?

This study utilized objective design attributes like the shape of a typical floor, location of the building's core, ground and top floor configurations and percentage of exterior windows, which were reviewed and identified by the authors using their prior design experience and practice. It is hoped that analysis utilizing these attributes will generate statistically significant results. Further discussion on these attribute measurements can be found in chapter IV.

It is helpful if objective measures are readily available or easily derivable data points. Fortunately, in this study, additional design attributes were collected from existing databases such as typical floor plate size, number of elevators, parking ratio, year built and year renovated. A wish list of design characteristics would include size of mechanical systems, capacity of telecommunications infrastructure, level of security, and energy usage per SF among other typical design attributes. However, a majority of these building metrics reside with individual property managers; some are not collected in a central location; or sometimes are not measurable.

Limitations of this definition

Although key design attributes like floor shapes (which impact the building mass), window to wall ratio (which proxies for both the amount of natural light as well as architectural glazing), core locations and presence of podium or tapered building mass (both reflect efficiency, floor configurations and mix of uses) along with the subjective design score for each property was captured in this study, it is not an exhaustive list of design attributes that constitute a "well-designed" office building. It is hoped that this research be a first brush stroke of what could (and should) be a more comprehensive study.

CHAPTER III: LITERATURE REVIEW

Factors influencing office building value

Several studies on office markets approach office building value through the measures of rents and vacancy, as predicted by attributes such as location, market conditions, building characteristics as well as lease characteristics. Within the existing body of literature, previous researchers have used structural characteristics, lease and location characteristics as independent variables for linear regression modeling. Structural characteristics include data points such as total building area, number of floors, building classification (Class A - Class C), building age, on-site parking, number of elevators, speed of elevators, availability of service elevators, building user amenities (like fitness clubs, onsite cafés, convenience stores, day care, etc). Location variables take into account distance from city center, suburban and urban classifications, distance from nearest highway interchange or transit stops, and tax rates. Lease variables include square feet of lease, lease length in years, etc.

Clapp[17] (1980) used a regression model to analyze the annual rental rate for 105 office buildings in Los Angeles on building attributes and three location variables (the distance to the CBD, average commute time for users in each building, and total office space within a two block radius). While all 3 variables were significant, the distance to the CBD had a larger positive relationship with rents than the other two variables. It was found that tenants are willing to pay a premium for being located in close proximity to LA's CBD.

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[17] *The Intrametropolitan Location of Office Activities* Journal of Regional Science, 1980 by Clapp, John M.

Mills (1992) analyzed office asking rents from 543 offices in and around Chicago, IL. Comprising of around 80% of the total office space within the Chicago MSA, building characteristics such year built, total square feet, minimum and maximum floor area in a property, vacancy rate, availability of on-site parking or neighborhood parking, building amenities (like restaurants, shops, fitness clubs) and historic landmark designation were gathered for the study. The results confirmed that asking rents are influenced by age, size of building, available amenities as well as its location. Separately, Bollinger et al.[18] (1998) found that the proximity to highway interchange or access commanded significant office premium, while being within walking distance of a train station did not.

Glascock, Kim, and Sirmans[19] (1993) studied the office building rents and rent adjustment. They found that rents varied across building class, location, market conditions, and contract differences. Employment levels and large building size also positively increase office rents. Colwell, Munneke and Trefzger[20] (1998) found that a substantially high premium was commanded by office buildings in defined employment centers.

Net operating income versus rents

All the studies mentioned above have analyzed impact of different factors on office building rent. Since architecture/design impacts both initial and operating costs, this study will

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[18] *Spatial Variation in Office Rents within the Atlanta Region* Urban Studies, 1998 by Bollinger, C.R., Ihlanfeldt, K.R. and Bowes, D.R.

[19] *An Analysis of Office Market Rents: Parameter Constancy and Unobservable Variables* Journal of Real Estate Research, 1993 by Glascock, J. L., M. Kim and C. F. Sirmans

[20] *Chicago's Office Market: Price Indices, Location and Time* Journal of Real Estate Economics, 1998 by Colwell, P., H. Munneke and J. Trefzger

deviate from using rents and analyze the impact of design on net operating income. The net operating income formula[21] is calculated as follows:

*Potential Gross Income (Rent * SF) (minus) Vacancy (plus) other income (parking, etc) (minus) Operating expenses = Net operating income*

NOI is a good measure of a building performance as it captures the effects of rents, vacancies as well as the operating expenses. For instance, a "well-designed" building may command high rents, but generate high operating expenses. In this case, the NOI due to the developer/owner/investor may effectively be low. In contrast, a "well-designed" building may command high rents, but consume lesser operating costs, in which case, the NOI to the developer/owner/investor is high. Therefore, if NOI is higher in "well-designed" buildings, it could imply that a) tenants are willing to pay a premium, or b) operating costs for those buildings are low, or c) both.

How much is good design worth?

There is small body of formal investigation that has incorporated certain design attributes into the office property value equation to ascertain the value-add of good design features. Three key studies done in the 80's and 90's have made significant inroads on the value of design. Hough and Kratz (1983) discovered a 21% higher rent premium for buildings with high-quality architecture. In their study, they determined buildings of high design quality based on awards garnered and landmark recognition. One key issue arises from this identification methodology. Although it identifies the best buildings in terms of architecture, it

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[21] *Commercial real estate analysis and investments* Australia; Mason, Ohio : South-Western Publishing (2001) by David M. Geltner, Norman G. Miller.

does not provide a clear understanding of how much incremental value one unit of design contributes to the building.

Extending the previous study, Vandell and Lane (1989) evaluated the extent to which architectural quality of a building contribute to its value (through the metric of rents). In contrast to Hough and Kratz, the design ranking for each property, in their study, was drawn from the paper survey completed by a panel of local architects. One of the key prerequisites for participating in their study was not only that the architects had sat on design awards juries but were familiar with all 102 properties. The design evaluation criteria takes account of external façade materials, fenestrations (the design and composition of openings on the external façade), massing (the physical volume and bulk of the building), design of public spaces (both interior and exterior), contribution to the city's skyline, response to surrounding context (in terms of use), public amenities. The architects in the evaluation panel[22] were provided with a photograph and map showing the site location of each property, and asked to rank the buildings on a 1 to 5 scale based on the above eight design criteria.

Their study suggested that building rents and vacancy period behaved as functions of both design and non design characteristics. They concentrated their study on 102 Class A office buildings (of over 100,000 sf) in the Greater Boston using site and location data as well as design rating and amenities for each property. The data used in the research such as quarterly rents and vacancy figures between 1979 and 1986 were gathered from Spaulding and Slye Office report. Other building level metrics such distance to the city center, availability of on-site parking, neighborhood parking number, total building area (square footage), number of floors, whether or not rehabilitation was done (and when) were compiled into a two page summary of each property.

Their results showed a strong influence of design on rents, with tenants paying a premium rent of almost 22% higher than for the buildings whose rating was the least. Their study also revealed that there was very little relationship between vacancy and design quality. Finally, their study showed that good design cost more to produce on average, but not necessarily in every case. Millhouse[23] (2005), which sought to understand if there is a private sub-market for "good" design, qualitatively found that good design commanded a price premium on a project.

In a related study conducted by Doiron, Shilling and Sirmans[24] (1992), the research centered on the trade-off between total rentable area in office buildings and a single design feature of office buildings - the atrium space within the building. They analyzed the relationship between the atrium, which acts as a public good within a building, and development cost to market rentable SF. Their research discovered that, for every decrease in unit development cost, the atrium space increased. The research also determined that, with a unit increase in market rents, the total atrium space decreased. The findings also suggest that a premium of 7% was paid by the tenants to rent spaces in office buildings with atriums, which illustrates that certain design attributes have a positive effect on rents.

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[22] the survey had a 35% response rate

[23] *Assessing the effect of architectural design on real estate values : a qualitative approach* MIT Thesis, 2005 by Jason A Millhouse

[24] *Do Market Rents Reflect the Value of Special Building Features?* Journal of Real Estate Research, 1992 by Doiron, J. D., J. D. Shilling and C. F. Sirmans

In a symposium[25] held by Harvard Design Magazine, a panel comprising of large real estate development company leaders were asked to share their thoughts on design and its contribution to improve life in cities. A number of panelists agreed that design was a critical component of their real estate projects. They expanded the definition of design to include both the aesthetic aspects as well as the functional aspects of a building, in order to create user satisfaction as well as support their long term investments. One important concern raised by the developers was trying to confront issues like "what is good design?" and "what is appropriate design?" The panelists agreed that having the architect on board at the earlier stages of project planning prevented the project from becoming a mediocre one. Although there was some discussion on the positive impact of "good" design for the project (and its neighborhood), no definitive remarks were made on the actual benefits of good design on building rents or NOI.

With the exception of the lease variables, this study includes many of the structural characteristics and location variables, used in earlier studies. For the purposes of this study, these structural characteristics will be referred to as "BLDG_INFO" in order to distinguish them from the objective building design attributes created by the authors.

[25] This article appeared in Harvard Design Magazine, Spring/Summer 2006, Number 24. The panelists were Ronald M. Druker, President, The Druker Company, Boston; Gayle Farris, President, ForestCity | Boston; Mark R. Goldweitz, President, Garrison Square Management, Inc., Boston; Ken Hubbard, Executive Vice-President, Hines Interests, Houston; Ronald Ratner, Executive Vice-President and Director, Forest City Development, Cleveland; Jonathan F. P. Rose, President, Jonathan Rose Companies, New York

CHAPTER IV: DATA DESCRIPTION AND METHODOLOGY

Data source

The raw data was gathered from 4 sources: extensive building data from a large portfolio of office properties, CoStar® Property Group, a subjective survey of 31 architects and quantifiable design characteristics created by the authors. Consisting of 547 individual building observations, the data set represents a large cross section of office buildings in over a dozen major US metropolitan areas and helped create a strong platform on which to build this research.

Office property portfolio and CoStar®

The base data, collected from the office property portfolio, consisted of average building level NOI from 2000-2005, floor by floor rentable SF, year built, building class and location (in the form of longitude and latitude).

The tools within CoStar® allowed for the collection of unique property level data such as the total number of daily employees within a one mile radius of each property, year renovated, number of elevators, parking ratio, detailed building floor plans and large exterior photographs of each property. The number of average daily employee within a one mile radius allows for an accurate measurement of centrality, location and market demand.

To control for location, each MSA's City Hall was selected as default city center, and the direct distance from City Hall to each property was calculated. Historically, City Hall has been considered the original seat of power and the center of a city's legislative and judicial branches. While many of the MSA's have grown in size and complexity since the construction of their City Hall, it still serves as a symbolic and/or administrative center. It should also be noted that certain MSA's within the data set such as Orange County, East Bay/Oakland and San Jose encompass many suburban cities and towns and that the historical growth pattern of cities do not apply to these MSA's. Another exception is Atlanta, where office rents in the suburban periphery are often higher than rents within Atlanta's CBD. Nevertheless, City Hall was selected as the "center" of each MSA because these locations were readily available and facilitated consistent data collection. However, it is unclear if the direct distance variable would prove significant in the study.

Creating the distance variable required the use of the ArcGIS Lab located within MIT's Rotch Library. Longitude and latitude data points for each property (to an accuracy of 6th decimal places) were collected from the office portfolio database, enabling the software to locate a property within +/- 4 feet. The longitude and latitude of each MSA's City Hall was calculated using Google Earth[26]. Calculating driving distances was considered but after performing several trial runs, it was found that the differential between direct and driving distances were not large enough to merit additional data gathering within ArcGIS.

The following table lists the data variables collected from the large office portfolio and CoStar®, along with the source and methodology.

Variable	Source	Description
noi	Portfolio	Average building level Net Operating Income from 2000-2005
total_sf	Portfolio	Total rentable square footage

[26]Google Earth combines satellite imagery and maps and provides geographic information http://earth.google.com/

Variable	Source	Description
noi_sf	Portfolio	Net Operating Income per total square feet
day_employ~t	CoStar	Number of daytime employees at a one mile radius from Property
class_a	Portfolio	Dummy variable: 1 of Class A, 0 if not Class A
num_floors	Portfolio	Total number of floors in a Property
_2006	Portfolio	Age variable: Property built from 1996-2006
_1995	Portfolio	Age variable: Property built from 1982-1995
_1982	Portfolio	Age variable: Property built prior to 1982
city_hall	Portfolio/ArcGIS	Direct distance from Property to each respective MSA's City Hall
renovation	CoStar	Dummy variable: 1 of renovated, 0 if not
elevator	CoStar	Number of public and service elevators
parking_ra~o	CoStar	Parking Ratio = parking spots / 1000 leasable sf
mkt_atlanta	Portfolio	Atlanta, GA MSA
mkt_boston	Portfolio	Boston, MA MSA
mkt_chicago	Portfolio	Chicago, IL MSA
mkt_oakland	Portfolio	Oakland/East Bay, CA MSA
mkt_la	Portfolio	Los Angles, CA MSA
mkt_orange	Portfolio	Orange County, CA MSA
mkt_sacram~o	Portfolio	Sacramento, CA MSA
mkt_san_di~o	Portfolio	San Diego, CA MSA
mkt_san_fr~o	Portfolio	San Francisco, CA MSA
mkt_san_jose	Portfolio	San Jose, CA MSA
mkt_seattle	Portfolio	Seattle, WA MSA

Exhibit 1 : Table of variables, sources and definitions - 1

Subjective design score

This subjective numerical ranking data set has been generated using an online survey. Participants were asked to rank a property's design on a scale of 1-10. Chapter V discusses the objectives, design, methodology and results of the subjective data in detail.

O b j e c t i v e d e s i g n m e a s u r e s

One of the key aspects of this research revolves around the objective measures of design. After reviewing building floor plans and "available suite floor plans" from CoStar®, building characteristics such as property's core[27] location (center or non-center), typical floor shape (square, rectangle, etc.) and percentage of exterior glazing were identified.

Evaluating floor plans

As mentioned earlier, most of the typical floor plans of the 296 properties were collected from the CoStar® database. The remaining typical floor plans for the properties were collected from the individual property websites. The properties were divided based on four major floor shape categories – square floor plan, rectangular floor plan, linear irregular floor plan, and curved irregular floor plan. Buildings with square floor plans were those with length to width ratio of external walls as approximately 1:1. Buildings with rectangular floor plans with length to width ratio of external walls as approximately 1:1.25 or more. Buildings with linear irregular floor plans were identified as those with more than 4 significant external walls but ran in a linear fashion. Examples for linear irregular floor plans include "L" shaped and "H" shaped building. Building with curved irregular floor plans were those that had one or more major external wall that was curved.

[27] The building core typically contains the elevators, service spaces, washrooms and chase spaces for ducts, wiring and plumbing, etc.

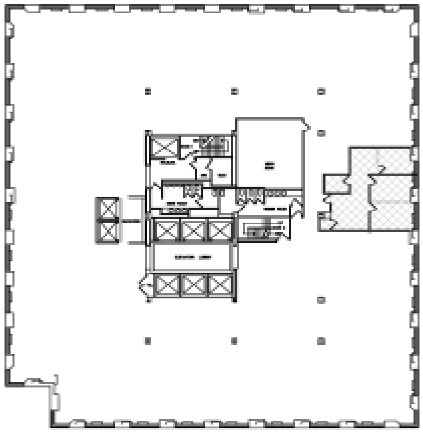

Exhibit 2 : Example for square floor plan

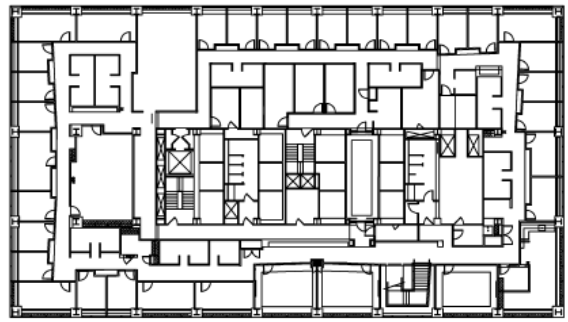

Exhibit 3 : Example for rectangular floor plan

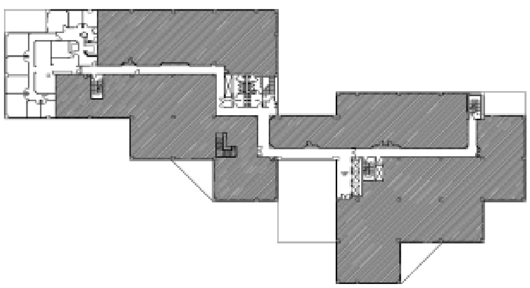

Exhibit 4 : Example for linear irregular floor plan

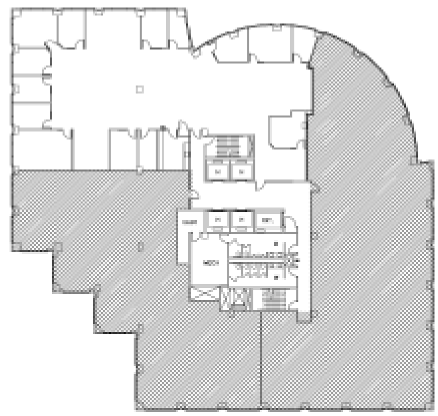

Exhibit 5 : Example for curved irregular floor plan

Evaluating core locations

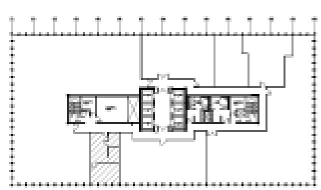

Exhibit 6 : Sample of center core

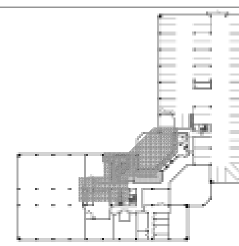

Exhibit 7 : Sample of non-center core

Upon reviewing floor plans, if the distant from the core to one external wall and the distance from the core to the opposite external wall was equal, the location of the core was considered to be central. If not, the property was considered to have a non-centrally located core. Additionally, if the core elements (like the escape stairs, bathrooms, etc) were dispersed in the floor, it was considered to be a non-central core.

Evaluating window to wall percentages

The percentage of exterior glazing generated the most discussion as the percentage of windows, from the tenants' perspective, was at times difficult to ascertain from a single exterior photograph. However, assuming that the photograph is a fairly close representation of the property's typical window configuration, four main categories were created – buildings with 0 to 29% windows, buildings with 30 to 59% windows, buildings with 60 to 89% windows and buildings with 90 to 100% windows. Using available marketing photograph of the property, the percentage of glazing on exterior walls, ignoring the spandrel glazing between the ceiling space and the finished floor, was determined.

Exhibit 8 : Sample building with 0 to 29% windows

Exhibit 9 : Sample building with 30 to 59% windows

Exhibit 10 : Sample building with 60 to 89% windows

Exhibit 11 : Sample building with over 90% windows

In summary, the following table lists the variable, source and methodology used to create the objective measures of design.

Variable	Source	Description
taper	Portfolio/Author	Using Portfolio rentable SF, if the average SF of top 3 floors divided by SF of a typical floor was less than 90% of the typical floor SF, then the property is considered to taper
broad_podium	Portfolio/Author	Using Portfolio rentable SF, if the average SF of bottom 3 floors divided by SF of a typical floor was equal to or greater than 110% of the typical floor, then the property was considered to contain a broad podium
core_center	Portfolio/Author	Evaluating typical floor plans, if the core of the building (elevators, elevator lobby, stairs, mechanical, electrical, plumbing and bathrooms) are centrally located, the property is categorized as **core_center**
core_non_ctr	Portfolio/Author	Evaluating typical floor plans, if the core of the building (elevators, elevator lobby, stairs, mechanical, electrical, plumbing and bathrooms) are not centrally located, the property is categorized as **core_non_ctr**
fl_square	Portfolio/Author	Evaluating typical floor plans, if the exterior shape of the building is a square, the property is categorized as **fl_square**
fl_rectangle	Portfolio/Author	Evaluating typical floor plans, if the exterior shape of the building is a rectangle, the property is categorized as **fl_rectangle**
fl_linear_~r	Portfolio/Author	Evaluating typical floor plans, if the exterior shape of the building is not square, rectangular, oval or circular but has orthogonal side (for example a "L" or "H" shaped building), the property is categorized as **fl_linear_~r** or Linear Irregular
fl_curved_~r	Portfolio/Author	Evaluating typical floor plans, if the exterior shape of the building is not square, rectangular, oval or circular but has a significantly curved side, the property is categorized as **fl_curved_~r** or Curved Irregular

Variable	Source	Description
win_0_29	CoStar/Author	Using the Architect survey photographs, the % of glazing on exterior walls from perspective of the tenants (spandrel glazing located within the ceiling space and below the finished floor was ignored) was determined. **win_0-29** = 0% to 29% glazing
win_30_59	CoStar/Author	Using the Architect survey photographs, we determined the % of glazing on exterior walls from perspective of the tenants (spandrel glazing located within the ceiling space and below the finished floor was ignored). **win_30-59 =** 30% to 59% glazing
win_60_89	CoStar/Author	Using the Architect survey photographs, the % of glazing on exterior walls from perspective of the tenants (spandrel glazing located within the ceiling space and below the finished floor was ignored) was determined. **win_60-89** = 60% to 89% glazing
win_90-100	CoStar/Author	Using the Architect survey photographs, the % of glazing on exterior walls from perspective of the tenants (spandrel glazing located within the ceiling space and below the finished floor was ignored) was determined. **win_90-100** = 90% to 100% glazing

Exhibit 12 : Table of variables, sources and definitions - 2

Data cleaning

The data set was reduced to 286 observations based on the following criteria:

i. Retail, industrial and flex office observations were deleted as they did not fall within the scope of the research.

ii. Observations which were sold or purchased between the years 2000-2005 were deleted due to incomplete recording of data.

iii. Observations with incomplete data were removed as they are unusable for statistical analysis.

iv. The scope of the research was limited to 11 MSA's which represented the majority of office property portfolio's NOI. This narrowing of observations also ensures that the maximum numbers of observations lie within each MSA to generate meaningful regression results, since Market Dummy Variables will be used. The selected MSA's include: Atlanta, Boston, Chicago, Oakland/East Bay, Los Angles, Orange County, Sacramento, San Diego, San Francisco, San Jose and Seattle.

v. The office portfolio data collection methodology was not consistent with CoStar® data collection methodology. A single line item within the office portfolio data set may represent either an individual property or a series of properties. For example, a single line item within the office portfolio may represent four individual office buildings in a suburban office park. Since CoStar® provides current information on available office space (by property), they list each individual building separately under the metric "Property ID". This discrepancy in data recording involves 9 observations within the office portfolio data set which correspond to over 40 individual building observations. To remedy the data inconstancies, the following strategy was adopted: If one office portfolio observation represents four uniquely sized office buildings within one office park, the total office park average NOI was proportionately divided based on the ratio of each buildings rentable sf to the total office park's rentable sf. The remaining data values (age, parking ratio, etc.) were gathered from CoStar®. Observations were dropped when the information to deconstruct each individual property's contribution to the office parks average NOI was not available or when the grouped properties did not exhibit consistent age, design, SF, number of floors, etc.

vi. The age of a property was converted into three variables, each representing a period of office development cycle in the US. Most properties developed during a particular building era would embrace modern construction methods and technologies, meet the needs of office tenants, and are representative of that era's architectural style. Following this logic, an office developer in 2006 can be expected not to build a new office building using the technology, market needs and style of the 1970's. Hence, the decision was made to divide the variable age into a tri-partite condition.

vii. CoStar® generated a wealth of current information on all properties which have space for lease as of July 2006. Consequently, the first pass at merging the office property portfolio data set with the CoStar® data set generated missing variables for over 100 properties. Since these properties did not have space for lease/sub-lease, CoStar® did not have photographs, plans, parking ratios or number of elevators. The missing variables were then sourced from the property owner's website.

Summary statistics

This section will describe in detail the statistics of the data set to provide a general understanding of the relative distribution of building characteristics. The following table outlines the basic statistics of NOI per SF, average daytime employment within one mile radius, distances to each MSA's city hall, total sf, number of floors, number of elevators and parking ratio. Across the 296 observations, the mean NOI per SF value is $22.56 with a standard deviation of $11.26 and a range from $5.16 through $87.89. The mean daytime employment is 63,853 employees with a standard deviation of 103,547 and a range from 1,613 through 552,399. The distance of properties to their respective city halls averages 9.9 miles and a standard deviation of 6.9 miles, with a range between 0.0 miles and 46.2 miles. Looking at a properties total SF, the average rentable SF of the data set comes in at 202,652 SF with a standard deviation of 229,176 and a range of 12,740 through 1,520,288 sf. Likewise, the total number of floors of each property average 9.1 with a standard deviation of 10.7 and a range from single story structure through 76 floor high-rises. Not surprisingly, elevators (service and passenger) also demonstrate a large range of 0 through a maximum of 40 with a mean of 4.3 and a standard deviation of 10.7. The final data point relates to parking ratio (number of parking spaces per 1000 rentable SF) with the data set producing a mean of 3.03, standard deviation of 1.29 and a range from 0 through 4.60.

	NOI_SF	Day_Employment	City_Hall	Total_SF	Num_Floors	Elevator	Parking_Ratio
Mean	22.56	63853	9.9	202652	9.1	4.30	3.03
Standard Error	0.65	6019	0.4	13321	0.6	0.32	0.08
Median	19.77	20827	11.2	124516	5.0	3.00	3.50
Mode	16.95	25381	15.2	56448	2.0	0.00	4.00
Standard Deviation	11.26	103547	6.9	229176	10.7	5.45	1.29
Sample Variance	126.83	10722001880	48.0	52521838059	113.8	29.69	1.67
Kurtosis	11.85	6	1.8	9	8.3	9.89	0.50
Skewness	2.80	3	0.7	3	2.6	2.78	-1.35
Range	82.73	550786	46.1	1507548	75.0	40.00	4.60
Minimum	5.16	1613	0.0	12740	1.0	0.00	0.00
Maximum	87.89	552399	46.2	1520288	76.0	40.00	4.60
Sum	6677.09	18900344	2918.589804	59985100	2703	1272.00	896.98
Confidence Level(95.0%)	1.29	11845	0.8	26215	1.2	0.62	0.15

Exhibit 13 : Descriptive statistics of NOI per SF, location variables, and other variables

H i s t o g r a m s

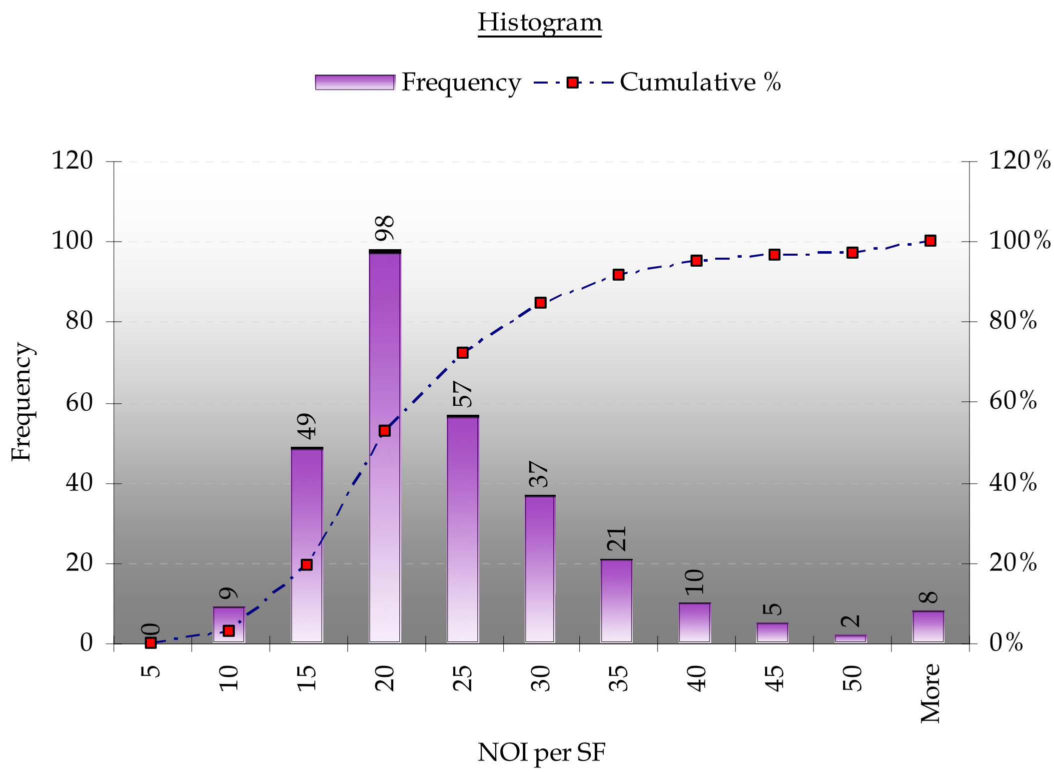

Exhibit 14 : Histogram – NOI per SF

The above histogram illustrates the distribution of NOI per SF with bins of $5 NOI/SF. It is clear that almost 95% of the properties generate less than $40 NOI/SF. It is to be noted that there are several outliers both at the low and high ranges of NOI/SF. Of the four properties with over $80NOI/SF, three are located in San Jose, CA and one is located in Los Angeles, CA. One explanation for their extremely high NOI/SF could be that the leases (for the three properties located within the heart of Silicon Valley) may have been signed at the height of the Tech Bubble[28]. When ignoring the extreme NOI/SF outliers, the data appears to be right skewed distributed with the bulk of the observations falling into the $15-$30 NOI/SF range.

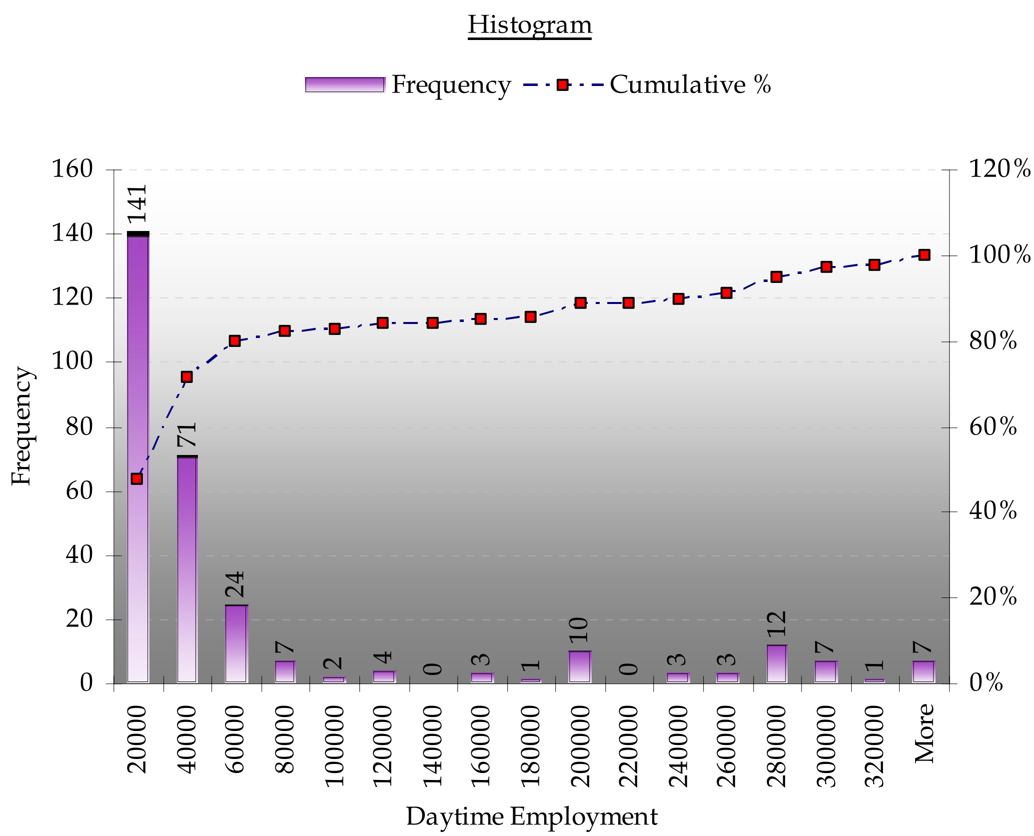

Exhibit 15 : Histogram – Daytime employment (bin size of 20,000)

The average daytime employment histogram above utilizing 20,000 bins shows that close to 80% of the properties within the data set are located in areas where average daytime employment at a one mile radius is less than 60,000 people. Less than 2.5% of the properties are located in areas where the average daytime employment at a one mile radius exceeds 320,000. Such high concentrations of daytime employees are typically only found in CBD's of large MSA's such as Chicago, IL (~550,000), San Francisco, CA (300,000) and Boston, MA (~290,000).

[28] Also known as the "dot-com" bubble. More information: http://en.wikipedia.org/wiki/Tech_bubble

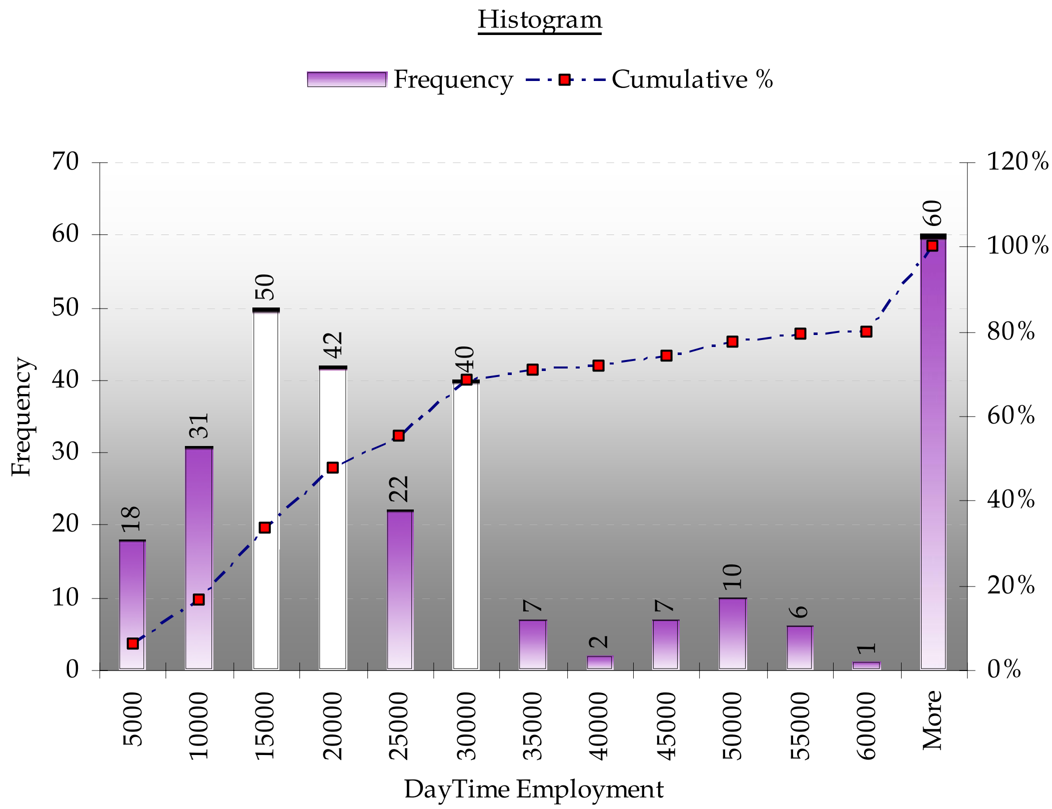

Exhibit 16 : Histogram – Daytime employment (bin size of 5,000)

To further review the day time employment factor, the histogram above shows bin sizes of 5,000 units. This reveals that 141 observations or 47.6% of the properties are located in areas where average daytime employment is less than 20,000 within a one mile radius. During the collection of employment data, it appears that several office parks were the only sources of employment at a one mile leading to the supposition that suburban office parks in the office building portfolio are at least one mile from other daytime employment centers.

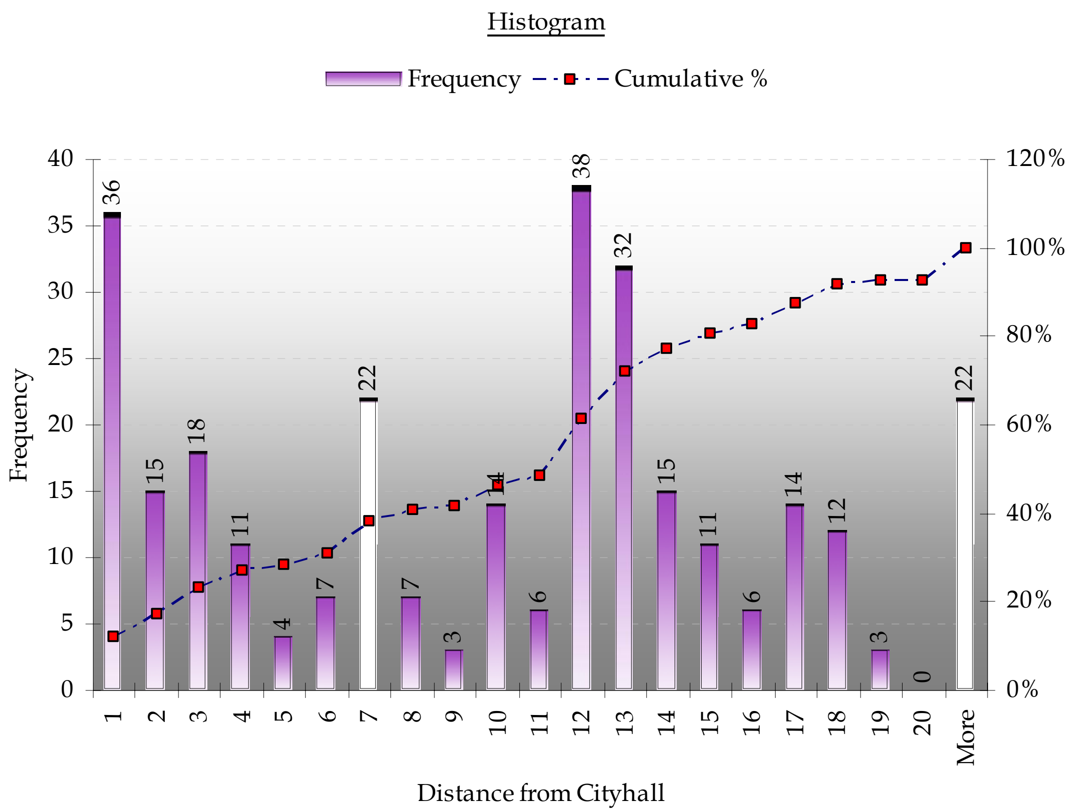

Exhibit 17 : Histogram – Distance from city hall

The histogram of each property's direct distance to its MSA's city hall using bin units of one mile appears to be multimodal distributed. The properties are distributed around 2 different distances: approximately 25% of the properties are located within 3-4 miles of each MSA's City Hall while 32% of the properties range in distance from 12-15 miles from City Hall. In addition, 7.4% of the properties are located in excess of 20 miles from City Hall. It can be said that the majority of the properties in this data set consist of suburban properties given the fact that only or 12.2% of the properties are situated within one mile of City Hall.

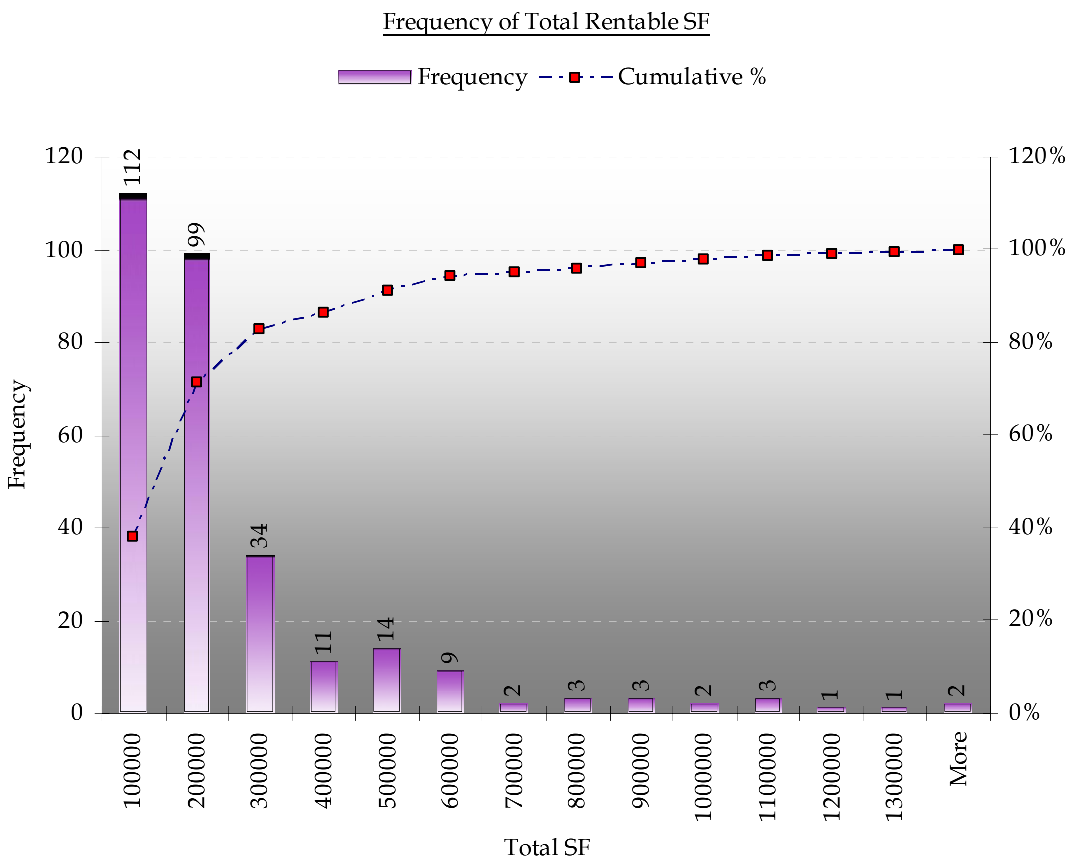

Exhibit 18 : Histogram – Total rentable square feet (bin size of 100,000 sf)

Using bins of 100,000 SF, the histogram above charts the distribution of rentable SF within each property. Almost 83% of the properties have less than 300,000 SF of rentable SF. There are nine observations with a total rentable SF above 1,000,000 SF and among this subset, the average distance to each MSA's city hall is 0.36 miles with a corresponding average daily employment of 290,326.

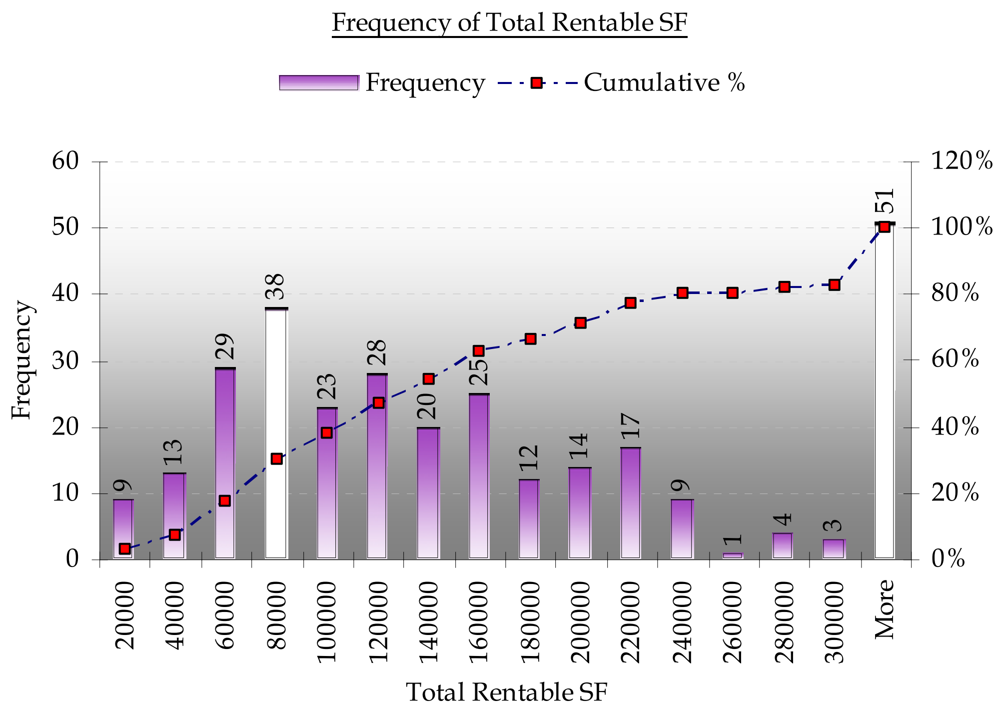

Exhibit 19 : Histogram – Total rentable square feet (bin size of 20,000 sf)

Reducing the bin size to 20,000 rentable SF results in the histogram above and when discounting properties above 300,000 sf, the data appears to be right skewed distributed peaking at 80,000 to 100,000 total rentable sf. 37.8% of the observations enclose less than 100,000 rentable SF, 33.45% of the observations contain between 100,000-200,000 rentable SF, 11.5% of the observations contain 200,000-300,000 rentable SF and the remaining 17.2% of the observation comprise of properties with rentable SF above 300,000.

Using the most common size distribution of 80,000-100,000 rentable SF (23 observations) results in the table below. Looking at the variables in questions, it can be concluded that the most common office property within this data set consists of Class A suburban office buildings constructed prior to 1995 with an average of 20,000 rentable SF, 4-5 stories in height which, on average, generated $18.78 NOI/SF from 2000-2005.

Variable	80,000 to 100,000	60,000 to 120,000
NOI_SF	18.78	21.01
Day_Employment	35036	31285.38
City_Hall	12.02	11.02
Class_A	78.3%	0.73
Total_SF	90264	87662.58
Num_Floors	4.434782609	3.83
Ave_SF_Fl	20354	22879.68
1996_2006	3	12.00
1982_1995	12	44.00
Pre-1982	17	33.00
Renovated	2	12.00
Elevators	1.78	1.82
Parking Ratio	3.47	3.39

Exhibit 20 : List of variables relative to observation size

When expanding this analysis to include properties with 60,000-120,000 rentable SF (89 observations), the most visible change is the increase in NOI/SF by $2.23. For the most part, the remaining quantitative building characteristics remain similar to the previous building size of 80,000-100,000 SF.

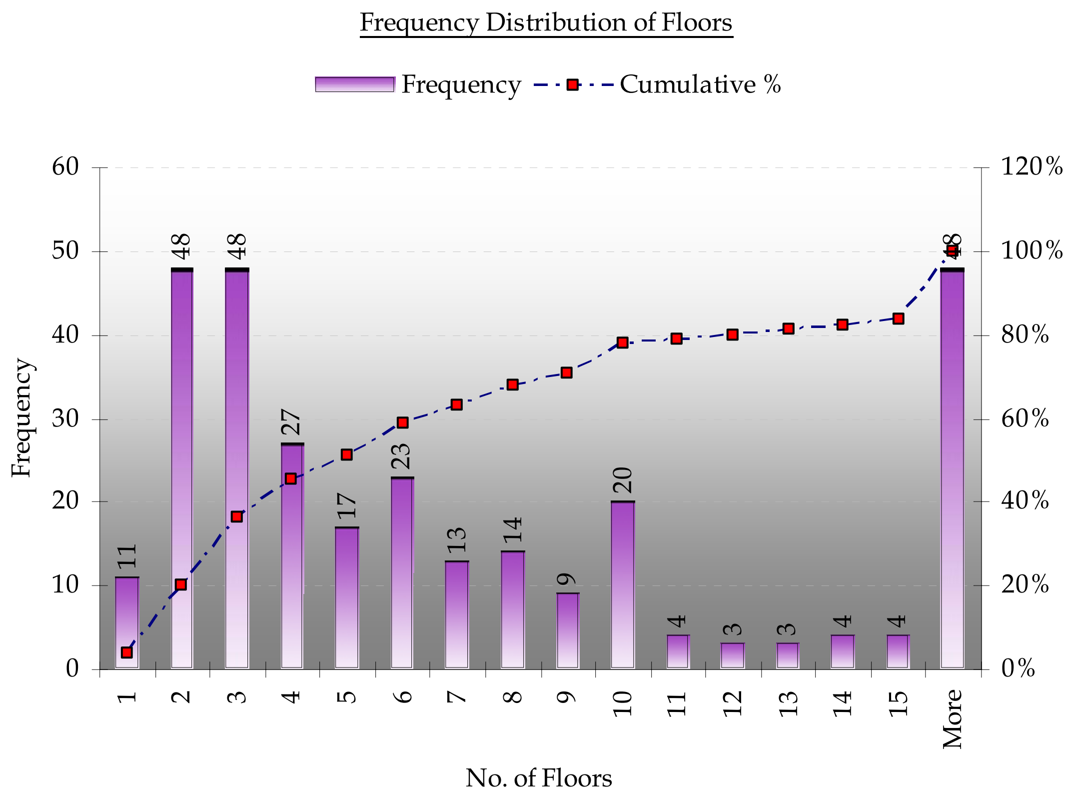

Exhibit 21 : Histogram – Number of floors

Upon reviewing the histogram distribution of floors using 1 floor as the bin unit, it can be seen that the majority of the properties contain 5 or less floors. Using the survey classification for low rise (1-4 floors), mid rise (5-12 floors) and high rise (+13 floors) results in a distribution of 45.3% of the properties classified as low rise, 34.8% of the properties classified as mid rise and the remaining 19.9% of the properties consisting of high rise properties. Discounting the high rise properties above 13 floors, the distribution of the sample appears right skewed. When reviewing the floor histogram in combination with the distance histogram, a strong argument can be made that this specific data set is skewed towards low and mid rise suburban properties.

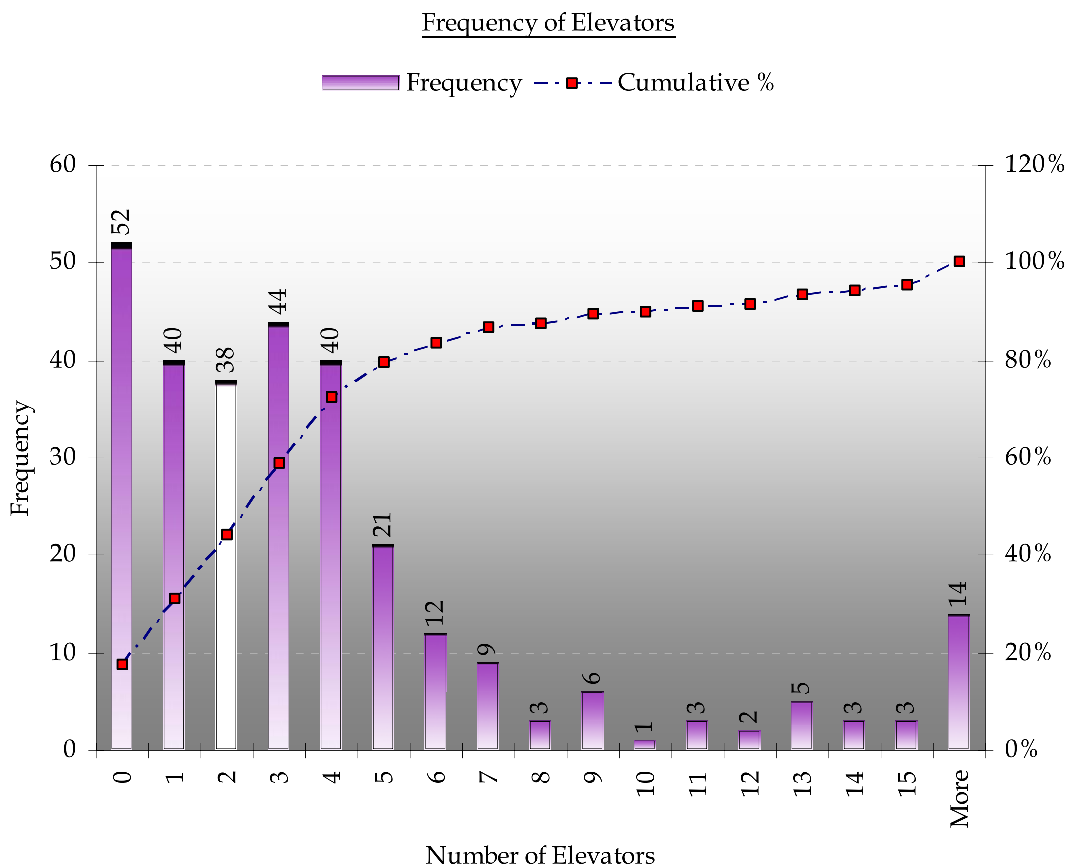

Exhibit 22 : Histogram - Number of elevators

The histogram above displays the frequency of elevators (both passenger and service). 17.6% (53 properties) of the observations do not include an elevator. Subtracting the number of observations with 1 floor (11) leaves 42 properties with more than 1 floor that do not include an elevator. With the equipment and supply needs of modern day office tenants, the data suggests that the 43 observations consist of older more functionally obsolescent properties.

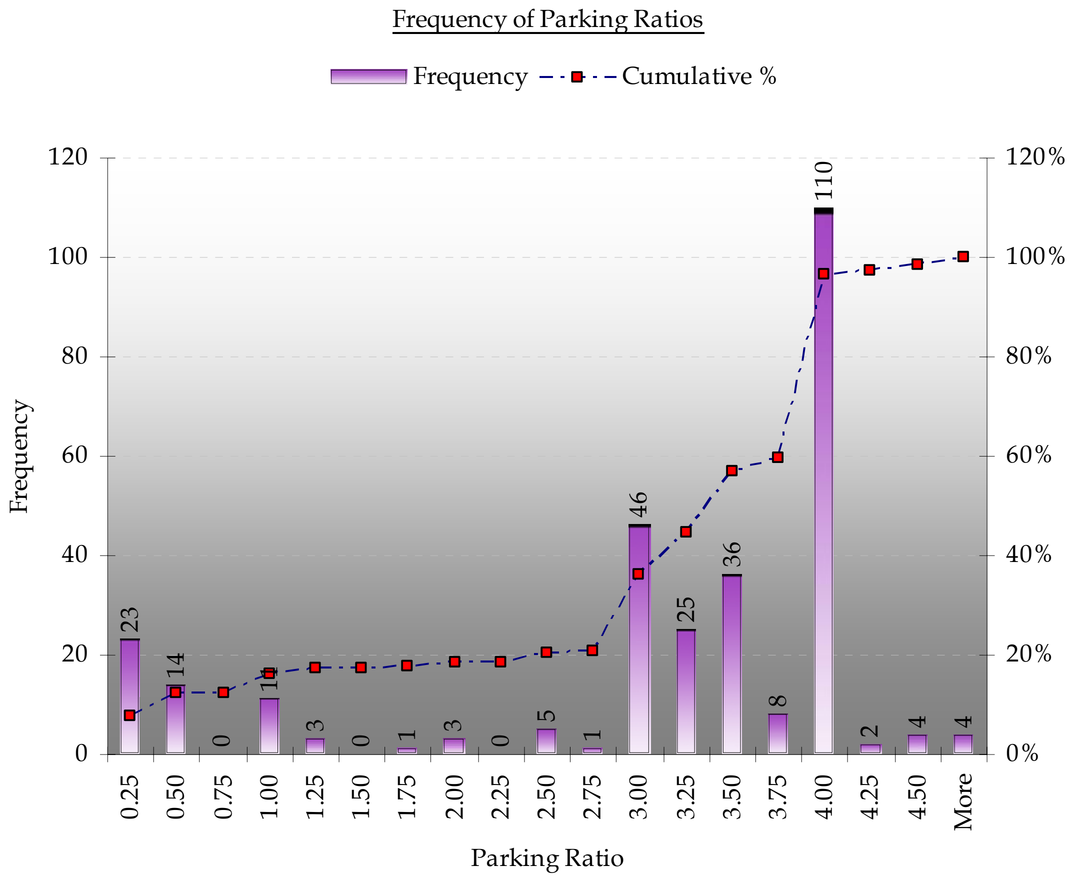

Exhibit 23 : Histogram - Parking ratio

The parking ratio histogram above suggests that there are blocks of parking ratios: less than 0.5 and from 3.35-4.25. The clusters of parking ratios match up with previous elevator, distance and number of floors histograms illustrating a low parking ratio presumably for properties in close proximity to City Hall and more typical 4.0 parking ratios for suburban office properties. The data also reveals that there are only 8 properties with parking ratios in excess of 4.25 and suggests a small demand from office tenants for parking ratios above 4.25.

Market	# Observations	Ave. NOI per SF
Atlanta	29	14.64
Boston	47	24.90
Chicago	29	17.49
Oakland	14	19.46
LA	31	23.79
Orange	32	16.85
Sacramento	9	17.45
San_Diego	9	18.56
San_Francisco	30	31.74
San_Jose	42	30.21
Seattle	24	20.02

Exhibit 24 : Number of observations and average NOI per SF in each MSA

Summary statistics: dummy variables

Within the 11 MSAs' represented in the data set, Sacramento, CA and San Diego, CA have a limited number of observations (9 each). East bay/Oakland, CA has the next lowest number of observations with 14. The remaining MSAs' have observations which range from 24 for Seattle, WA through to 47 observations for Boston, MA. Atlanta, GA and Chicago, IL each contain 29 observations, San Francisco, CA has 30 observations, Los Angeles, CA has 31 observations, Orange County, CA has 32 observations and San Jose, CA has 42 observations.

Summary statistics: office portfolio and CoStar®

Of the 296 observations, 235 have been designated Class A properties leaving 61 properties which carry a class B or C title. It should be noted that there is no industry wide standard in which to derive the class designation of a property. The data used in this research have been collected from CoStar®, which typically receives the property classification statistics from the property owners.

Variable	# Observations	% of Observations
Class_A	235	79.4%
Non_Class_A	61	20.6%

Exhibit 25 : Dummy Variable – Class A

When reviewing the age of the properties, 138 properties were constructed from 1982 through 1995 while 120 properties constructed prior to 1982 and 38 properties constructed post 1995. As part of the data cleaning procedures described in previous chapters, observations which did not contain complete building level NOI data from 2000-2005 were deleted. The 38 observations only contain recently completed buildings from 1996 through 2000. Recent studies have demonstrated that, within newly constructed properties, tenants are willing to sign leases with rents which are above market, which results in a new building lease premium. By utilizing average 2000-2005 NOI, it is hoped that the effects of new building leases will be minimized on the research.

Variable	# Observations	% of Observations
1996_2000	38	12.8%
1982_1995	138	46.6%
1890_1982	120	40.5%

Exhibit 26 : Dummy Variable – Age

Renovations on properties typically occur to stave off functional obsolescence of older properties and to meet the needs of the market. For the purposes of this research, the year a property was renovated was less important than the fact that a renovation took place. Of the 60 renovation observations, close to 75% of the properties had been renovated post 1995 and only 1 property was renovated prior to 1982. Consistent with the logic of renovations, 44 of the 60 renovation observations occurred on properties older than 1982.

Variable	# Observations	% of Observations
Renovation	60	20.3%
No_Renovation	236	79.7%

Exhibit 27 : Dummy Variable – Renovation

Summary statistics: objective measures of good design

Progressing with the analysis of quantitative measures of the physical building level characteristics, the vast majority of the observations contain neither a tapered top nor a broad podium. In simplistic terms, 221 observations have perfectly vertical exterior walls which have been 'extruded' from the floor plans. Perhaps due to the concentration of suburban properties, only 26 observations include a broad podium level close to the ground floor which could include various functions such as large multistory lobbies, retail or service based businesses. The limited number of broad podium observations is not surprising given the necessary site, surrounding and density requirements to justify the cost of developing unique ground floor levels.

Variable	# Observations	% of Observations
Broad_Podium	26	8.8%
Non_Broad_Podium	270	91.2%

Exhibit 28 : Dummy Variable – Broad Podium

The physical opposites of broad podium are tapering top floors (which occur in 66 observations). This physical characteristic is not constrained by density or site characteristics akin to broad podium and is more likely utilized where zoning, code or aesthetic concerns drive development decisions.

Variable	# Observations	% of Observations
Taper	66	22.3%
Non_Taper	230	77.7%

Exhibit 29 : Dummy Variable – Taper

206 properties contain the typical central location for the core. Consisting of elevators, service spaces, washrooms and chase spaces for ducts, wiring and plumbing, the prototypical low rise building locates the core centrally for efficiency. As buildings rise in height, the efficiency rational gives way to structural considerations as wind loading on mid rise and high rise buildings is of primary concern. Typically, a central core gives better structural stability against wind loads in buildings. Following this logic, 80 of the 99 rectangular floor plan observations hold central cores and 23 of the 31 square floor plan observations hold central cores. Due to floor plate size (either very small or very large), site plan, access considerations and building codes, several prototypical rectangle and square observations hold non-center cores.

Variable	# Observations	% of Observations
Core_Center	206	69.6%
Core_Non_Ctr	90	30.4%

Exhibit 30 : Dummy Variable – Core Center

Typical rectangle or square floor plans consist of roughly 43.9% of the observations. 12.8% of the observations hold curved floor plans while the remaining 43.3% of the observations have been categorized as linear irregular plans. It should be noted that, with the concentration of suburban observations, the distribution between typical square and rectangle floor plans and non-typical floor plans are very similar.

Variable	# Observations	% of Observations
Fl_Square	31	10.5%
Fl_Rectangular	99	33.4%
Fl_Linear_Irregular	128	43.2%
Fl_Curved_Irregular	38	12.8%

Exhibit 31 : Dummy Variable – Floor Plate Shape

When discussing window percentage distributions, it is clear that the majority of the observations contain windows to wall ratio[29] between 30-90%. Not surprisingly, there are 27 observations with less than 29% window coverage. This small sample size reinforces the generally accepted thought that office tenants prefer space with more daylight. On the opposite end of the spectrum, 27 observations contain more than 90% windows.

Variable	# Observations	% of Observations
Win_0_29	27	9.1%
Win_30_59	122	41.2%
Win_60_89	120	40.5%
Win_90_100	27	9.1%

Exhibit 32 : Dummy Variable – Exterior Window Percentage

Log linear regression

Regression is a statistical tool used to determine the extent to which one independent variable is related to multiple dependent variables. Since the data set consists of more than 16 variables, Stata® 8.0[30] was used to determine the mathematical relationships between the dependent and independent variables. Since the research is two-fold, multiple linear regressions were run with the natural logs of the dependent variables. The natural log of the dependent variable produces regression results where the independent variable's coef-

[29] from the tenant's perspective. In other words, as seen from the interior of the office space looking out.

ficient represents a constant percentage effect in the dependent variable. For example, if the dependent variable is "NOI per SF", dummy variable is "Rectangular Floor Plate" and the independent variable "Curved Floor Plate" has a statistically significant coefficient of 0.12, one could say that the data shows that a "Curved Floor Plate" generates 12% more "NOI per SF" than a "Rectangle Floor Plate". Linear regression analysis was used as the primary statistical tool in this research to test the cross-sectional relationship between design characteristics and average building NOI from 2000 through 2005.

Dependent variables

This research concentrates on a subjective survey of professionals and a quantitative analysis of building characteristics which results in 3 log linear regressions. The results of utilizing "Raw Survey Scores" and "Average Survey Scores" as dependent variables are discussed in Chapter V. The results of using "NOI per SF" as the dependent variable are discussed in Chapter VI.

Dummy variables

Dummy variables were generated for building class, age, renovation, MSA location and multiple architectural building characteristics. The following chart shows the dummy variables which were used as the default dummies for all 3 log linear regressions along with the total number of default dummy observations for each characteristic.

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[30] Stata is a statistical software used data analysis, data management, and graphics. Source: http://www.stata.com/products/overview.html

Dummy variables	# Observations
Not Class A	61
1959_1981	114
MKT_Chicago	29
No Podium	270
Core Center	206
Fl_Rectange	99
Win_30_59	122

Exhibit 33 : List of default dummy variables and quantity

Variable eliminations

Multiple log linear regressions were run using different combinations of independent variables to generate the final regression statistics. The basic strategy was to eliminate independent variables which did not have explanatory powers. In other words, if there was very little difference between regressions which included "Number of Elevators" as an independent variable and a second regression which deleted "Number of Elevators" as a variable. Understanding that, within our data set, the variable "Number of Elevators" does not influence the regression results, it was eliminated. Also, the following variables were eliminated using the methodology described previously: **city_hall** (City Hall), **num_floor**s (number of floors), **renovation**, **elevator** and **parking_ratio**.

City Hall: Perhaps due to the particular structure of the data set, which is weighted with suburban properties, the City Hall variable did not generate statistically significant results. In addition, certain MSA's within our data set demonstrate inverse NOI gradients – in other words, properties which are located closer to City Hall NOI for less than properties further from City Hall. For example, Atlanta office rents are consistently higher in certain suburban locations when compared to the CBD. Finally, the immediate area surrounding a City Hall may be subject to highly restrictive local zoning regulations in order to preserve the historic character of a MSA's City Hall. With limited density and older office stock surrounding a historic City Hall district, office developers and tenants have over time elected to agglomerate away from City Hall.

Number of Floors: This variable is highly correlated with the variable Total SF and was deleted.

Renovation: When included in regressions, this variable produced a negative coefficient – in other words, renovated properties generated less NOI per SF than buildings which had not been renovated. Perhaps due to the limited number of renovated observations, the behavior of this variable is contradictory to expectations and statistically insignificant.

Elevator and Parking Ratio: Since both variables were not statistically significant and did not possess explanatory powers, they were eliminated.

CHAPTER V: CAPTURING THE SUBJECTIVE MEASURE OF DESIGN

One of the goals of this research is to create a framework in which to measure the design quality of a property. Vandell and Lane (1989) used a paper-based survey to evaluate the architectural quality of 102 Class A office buildings situated within Greater Boston. The properties were ranked on a scale of 1-5 using 8 design criteria by 28 architects who had served on Boston area awards panel. Drawing on this previous research, an online survey was created to capture subjective rankings of a much larger sample of office properties located across several MSAs.

Survey intention and methodology

Understanding that good design is highly subjective, the survey was designed to gather ranking data, as perceived by practicing architects, for 296 properties to help identify properties (within our data set) as "better-" or "poorly-" designed. Additionally, two variables can be extracted from the survey results, which were subsequently used in the regression analysis. The average raw scores (AVE_RW_SCORE) and average scaled scores (AVE_SC_SCORE) were expected to be correlated with some of the quantitative building variables.

The respondents were briefed on the intent of the research and were advised to rank the design quality of the buildings based on their professional experience. The survey was anonymous and took on average 45-60 minutes to complete. The survey response rate was at a high 88% (31 out of 35 survey respondents). The survey contained 417 properties that were divided into 3 sections. Section 1 contained 217 low rise[31] buildings. Section 2 contained 127 mid rise[32] buildings and section 3 contained 73 high rise[33] buildings. The classification[34] of the properties is as follows:

i. Low rise office buildings – 1 to 4 floors above grade level

ii. Mid rise office buildings – 5 to 12 floors above grade level

iii. High rise office buildings – 13 floors + above grade level

Each section of the survey began with a sequence of 10 dummy[35] office properties which were not located within the 11 MSA's covered in our data set. Each question included a single marketing photograph[36] of a property and a ranking scale from 1 to 10 (representing 10% increments of design quality). The photographs were collected from CoStar® and are the same photographs displayed to prospective tenants and brokers searching for office space.

Out of the 417 properties in the survey, only 296 properties had relevant data and information (in terms of NOI per SF, market location, etc) required to run a robust regression analysis. Hence, the remaining 127 properties and their associated survey results were eliminated. The final observation break up across building height categories is as follows:

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[31] buildings of one to four stories and typically require no elevators

[32]"Mid rise building is typically 50-150 feet tall (approximately 5-12 stories)" - www.sanjoseca.gov/planning/design_guidelines/Chap_26%20Mid-and_%20High-rise.pdf

[33] "High-Rise Housing is typically 150 feet or taller (more than 12 stories)" – ibid.

[34] According to the Commonwealth of Massachusetts State Building Code (780 CMR), 6th edition, all buildings more than 70 feet in height above mean grade are considered high-rise buildings (780 CMR 403.1). The Massachusetts Building Code is based on the 1993 edition of the Building Officials and Code Administrators (BOCA) National Building code and is most prevalent in the Northeast USA. There are 3 other 'typical' building codes used within the USA that define "high-rise" slightly differently.

[35] These 10 property images were inserted at the beginning of each section to allow the survey respondents to establish their individual ranking methodology before continuing to rank the properties in the data sample. The results for these properties were eliminated once the survey was closed.

[36] Each image contained the principal façade of a property as displayed in the CoStar® database or in property owner's website.

Properties in sample data	296
Low rise properties	135
Mid rise properties	102
High rise properties	59

Exhibit 34 : List of building categories and observations

Survey participants and background

The ideal survey participant for this research would be senior architects with an excess of 20 years experience in US office design and construction. Given typical low response rates for blind surveys and the time commitment necessary to rank close to 400 properties, it was not feasible to reach a sufficient number of senior level architects to generate a statistically significant response pool. Consequently, the survey respondents were selected utilizing the following guidelines:

i. Respondents to have earned either a 5 year professional undergraduate degree or 3 year professional graduate degree in architecture

ii. Have a minimum of 3 years of work experience as a designer or architect

Survey participant background information is detailed in the charts below:

Particpants	No. of years of work experience	US or non-US Experience	US or non-US school	US or non-US raised	Completed graduate studies	Designed office buildings
Participant 1	10	US	Non-US	Non-US	Yes	Yes
Participant 2	4	US	US	US	Yes	No
Participant 3	3	Non-US	Non-US	Non-US	No	No
Participant 4	8	US	US	US	Yes	Yes
Participant 5	5	Non-US	Non-US	Non-US	Yes	Yes
Participant 6	7	US	Non-US	Non-US	Yes	Yes
Participant 7	7	Non-US	Non-US	Non-US	No	Yes
Participant 8	5	US	Non-US	Non-US	Yes	Yes
Participant 9	7	Non-US	Non-US	Non-US	No	No
Participant 10	8	US	US	US	Yes	No
Participant 11	10	US	Non-US	Non-US	Yes	Yes
Participant 12	4	US	US	US	No	Yes
Participant 13	5	US	US	Non-US	Yes	Yes
Participant 14	3	US	US	Non-US	Yes	No
Participant 15	9	US	US	US	No	Yes
Participant 16	5	US	US	US	Yes	Yes
Participant 17	6	US	US	Non-US	No	Yes
Participant 18	3	US	US	US	Yes	Yes
Participant 19	4	US	US	US	No	No
Participant 20	6	US	US	Non-US	No	Yes
Participant 21	8	US	US	US	Yes	Yes
Participant 22	3	Non-US	US	Non-US	Yes	Yes
Participant 23	4	US	US	Non-US	Yes	Yes
Participant 24	3	Non-US	US	Non-US	Yes	No
Participant 25	4	Non-US	US	Non-US	Yes	No
Participant 26	6	Non-US	US	Non-US	Yes	Yes
Participant 27	4	Non-US	US	Non-US	Yes	Yes
Participant 28	4	US	US	Non-US	Yes	Yes
Participant 29	3	Non-US	US	Non-US	Yes	No
Participant 30	7	US	US	US	No	Yes

Exhibit 35 : List of survey respondents' background and related information

As evident above, the survey respondents in general represent a group of younger architects with an average of 5.5 years work experience. One-thirds (32.3%) of the respondents come from the US. The rest of the respondents are from Asia and Europe. A majority of the respondents (70%) have received their graduate or undergraduate education in architecture in the US. Two thirds of the respondents have worked as architects in the US, have completed graduate studies and/or designed office buildings.

Out of the 21 architects who have prior experience designing office buildings, 16 are located in the US. 10 respondents have been raised, educated and are located in the US (see table below). The average work experience for this group is over 6 years.

Particpants	No. of years of work experience	US or non-US Experience	US or non-US School	US or non-US Raised	Completed graduate studies	Have you designed office buildings
Participant 2	4	US	US	US	Yes	No
Participant 4	8	US	US	US	Yes	Yes
Participant 10	8	US	US	US	Yes	No
Participant 12	4	US	US	US	No	Yes
Participant 15	9	US	US	US	No	Yes
Participant 16	5	US	US	US	Yes	Yes
Participant 18	3	US	US	US	Yes	Yes
Participant 19	4	US	US	US	No	No
Participant 21	8	US	US	US	Yes	Yes
Participant 30	7	US	US	US	No	Yes

Exhibit 36 : List of respondents raised, educated and working in the US

Four out of 31 respondents have been raised, educated and are located outside the US (see table below). The average work experience for this group is around 5.5 years.

Particpants	No. of years of work experience	US or non-US Experience	US or non-US School	US or non-US Raised	Completed graduate studies	Have you designed office buildings
Participant 3	3	Non-US	Non-US	Non-US	No	No
Participant 5	5	Non-US	Non-US	Non-US	Yes	Yes
Participant 7	7	Non-US	Non-US	Non-US	No	Yes
Participant 9	7	Non-US	Non-US	Non-US	No	No

Exhibit 37 : List of respondents raised, educated and working outside the US

Twelve out of 20 respondents (who were raised outside the US) have been educated in the US. The average work experience for this group is over 4 years.

Particpants	No. of years of work experience	US or non-US Experience	US or non-US School	US or non-US Raised	Completed graduate studies	Have you designed office buildings
Participant 13	5	US	US	Non-US	Yes	Yes
Participant 14	3	US	US	Non-US	Yes	No
Participant 17	6	US	US	Non-US	No	Yes
Participant 20	6	US	US	Non-US	No	Yes
Participant 22	3	Non-US	US	Non-US	Yes	Yes
Participant 23	4	US	US	Non-US	Yes	Yes
Participant 24	3	Non-US	US	Non-US	Yes	No
Participant 25	4	Non-US	US	Non-US	Yes	No
Participant 26	6	Non-US	US	Non-US	Yes	Yes
Participant 27	4	Non-US	US	Non-US	Yes	Yes
Participant 28	4	US	US	Non-US	Yes	Yes
Participant 29	3	Non-US	US	Non-US	Yes	No

Exhibit 38 : List of respondents raised outside US but have been educated/working in US

As demonstrated above, most of the respondents have been exposed to the US office market either professionally and/or academically.

Average raw and scaled score variables

As mentioned earlier, 31 completed responses were received out of total of 35 survey invitations. After reviewing the results, three outliers were eliminated (2 responses had very low average scaled scores and 1 response had very high average scaled score).

For ease of interpretation, the raw response data was scaled. The scaled score, which spanned from 1 (indicating poorly-designed building) to 10 (indicating well-designed building), aids in understandability and interpretation. The following method was used to generate the scaled scores:

i. the lowest (minimum) raw score by the respondent was assigned a score of 1

ii. the highest (maximum) raw score by the respondent was assigned a score of 10

iii. all raw scores between the minimum & maximum were calculated using the formula

$$new\_Scaled\_Score = 1 + \left(\frac{9}{\max_r - \min_r} \right) \times \left(Score_r - \min_r \right)$$

Where $\max_r$ is the maximum/highest raw score provided by the respondent

$\min_r$ is the minimum/lowest raw score provided by the respondent

And $Score_r$ is the raw score for the selected property

The raw and scaled scores were subsequently averaged to get the average raw score (AVE_RW_SCORE) and the average scaled score (AVE_SC_SCORE) for each property.

Survey results and analysis

First level analysis based on the average scaled scores showed very little variation across MSAs, building class, age and several other factors.

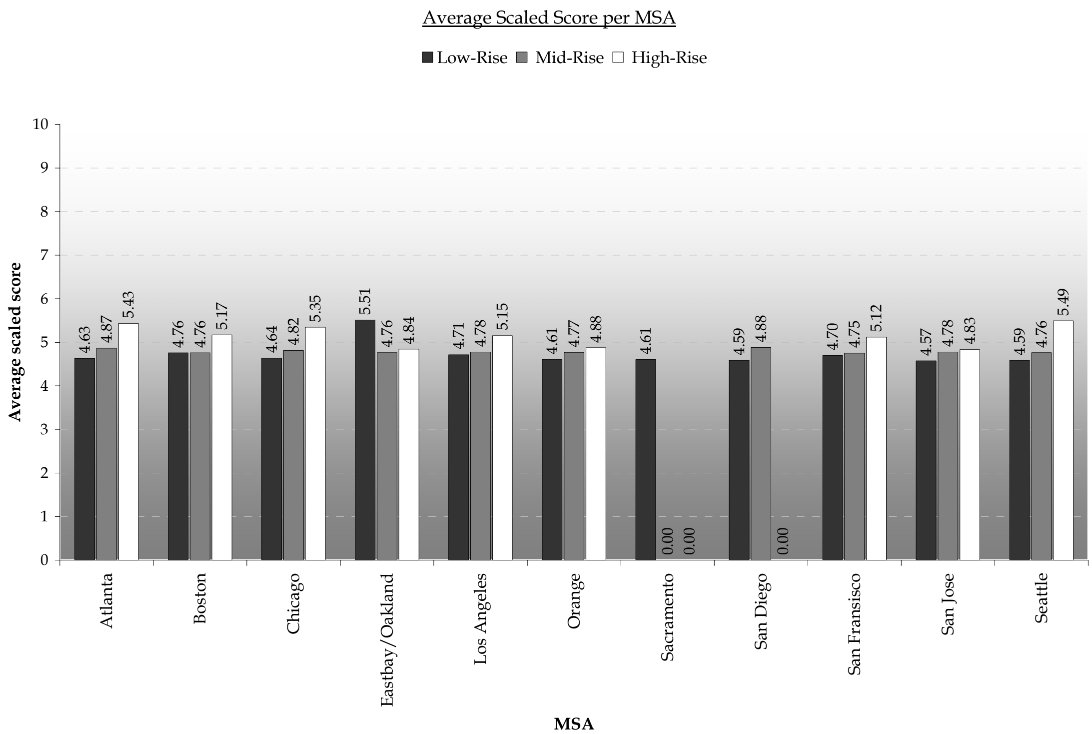

Exhibit 39 : Chart showing average scaled score per MSA

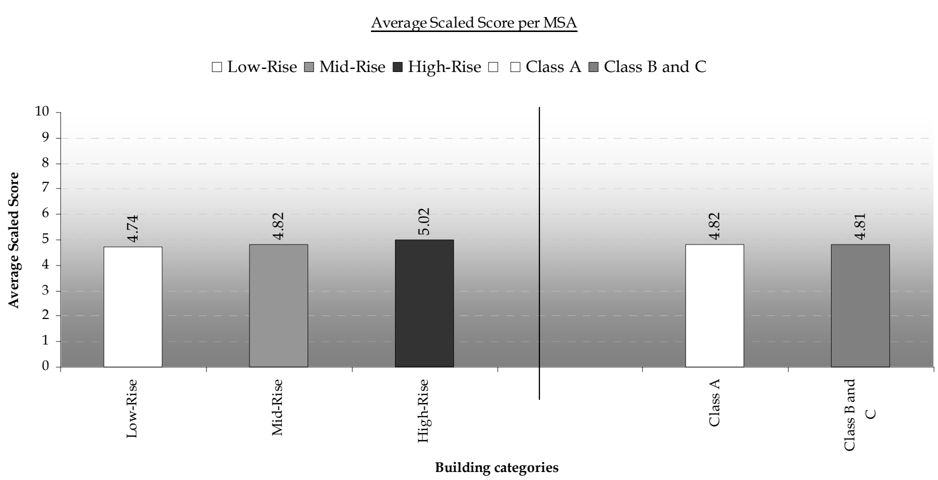

Exhibit 40 : Chart showing average scaled score across building categories and class

As evident in the previous chart, the average scores for the properties across MSAs[37] lie between 4.5 and 5. High rise properties in several MSAs (like Atlanta, Boston, Chicago, LA, SF and Seattle) were ranked higher, while low rise properties were ranked higher only in East bay/Oakland. Also, there was very little variation in scores due to building categories as well as building class. These results indicate that, on average, most of the architects ranked the design quality of the properties below average. This surprising result demonstrated a need to analyze and understand the scores in more detail.

One reason for the fuzziness of the responses was suspected to be the ambiguity caused by a camp of respondents who ranked the buildings very high and another camp of respondents who ranked the building very low, thus, canceling each other out. A four-step analysis was followed to investigate this further.

Descriptive statistics of average scaled scores

Average Scaled Score	
Mean	4.77
Standard Error	0.05
Median	4.76
Mode	3.57
Standard Deviation	0.88
Sample Variance	0.77
Kurtosis	0.77
Skewness	0.49
Range	5.87
Minimum	1.98
Maximum	7.84
Sum	1410.89
Count	296.00
Confidence Level(95.0%)	0.10

Exhibit 41 : Descriptive statistics of average scaled score

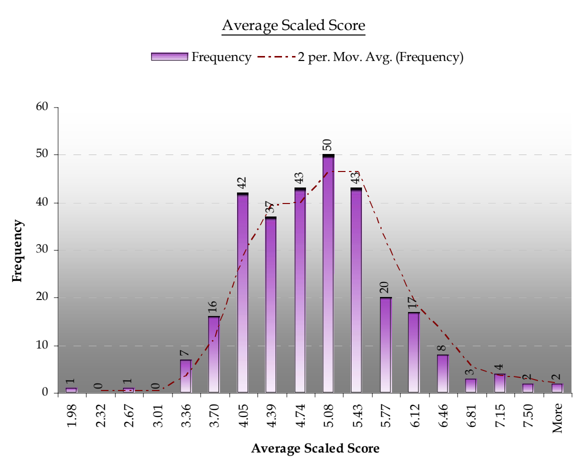

Exhibit 42 : Histogram for average scaled score

[37] Sacramento contained no mid-rise or high-rise properties within the data sample used. Also, San Diego contained no high-rise buildings within the data sample.

The descriptive statistics for the average scaled score, the mean score for the survey was 4.77 (with a low standard error of 5%) which is below the mid score scale of 5 indicating that, on average, a majority of survey respondents found the sample properties below average in terms of design quality. The standard deviation tells that 88% of the respondents' scores are clustered around the mean. In order to understand the skewness of the AVE_SC_SCORE variable, a histogram was created (exhibit 24).

The first observation was the spike (with a score value of 4.05) in the histogram graph. This can be explained by the fact that a score of 4 (approximately) could be a common ranking of design quality, so survey respondents whose ranking were perhaps a little less than or a little greater than average might be inclined to choose 4.

The second observation is a normal distribution of average scaled scores in the histogram. The average scales score do not exhibit bimodal behavior, ruling out the "two-camp" notion. Typically, a bimodal distribution is a distribution with two different peaks — that is, there are two distinct values (modes) that measurements cluster around. Since the AVE_SC_SCORE variable represents a reported preference of an individual, bimodality may have indicated a polarization of opinions. As a double check, the above analysis was done with the raw scores as well (Exhibit 25 & 26). The results showed similar statistical behavior.

Average Raw Scores	
Mean	4.32
Standard Error	0.03
Median	4.32
Mode	4.77
Standard Deviation	0.56
Sample Variance	0.32
Kurtosis	0.96
Skewness	0.53
Range	3.61
Minimum	2.65
Maximum	6.26
Sum	1279.61
Count	296.00
Confidence Level(95.0%)	0.06

Exhibit 43 : Descriptive statistics of average raw Score

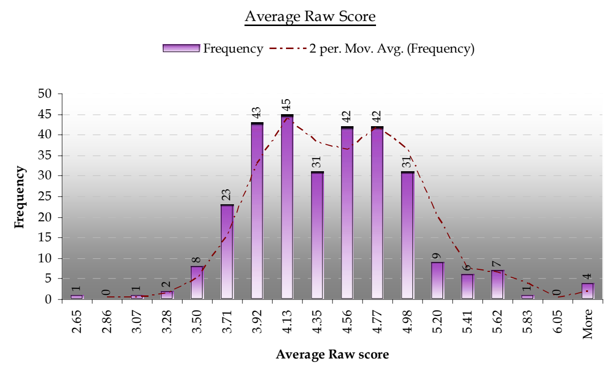

Exhibit 44 : Histogram for average raw score

Correlation matrix of average scores

Step two was to create a correlation matrix, with each respondent's individual scores with respect to others. Typically, in correlation matrices (and the associated scatter plots) the values can vary between -1 (perfect negative correlation), through zero (no correlation), to +1 (perfect positive correlation). The closer the correlation coefficients are to zero, lesser the extent to which the two variables are related. In the following exhibit[38], the numbers represent the correlation coefficients and the mirror boxes represent the correlation plots. The fuzziness of the plot increases as the correlation coefficient drops closer to 0.

[38] Simple example of linear correlation: 1000 pairs of normally distributed numbers are plotted against one another in each panel (bottom left), and the corresponding correlation coefficient shown (top right). Along the diagonal, each set of numbers is plotted against itself, defining a line with correlation +1. Five sets of numbers were used, resulting in 15 pair wise plots. Image Source: http://en.wikipedia.org/wiki/Image:Corr-example.png

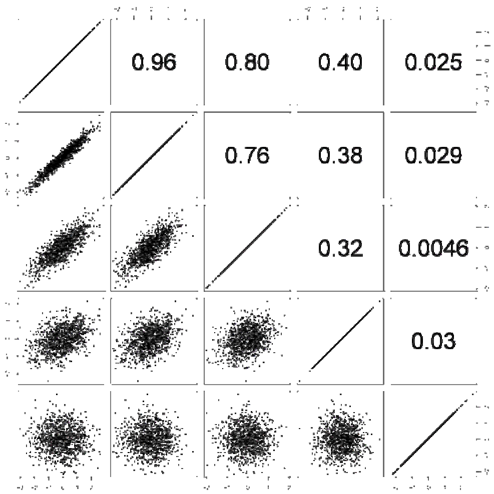

Exhibit 45 : Scatter plots of sample correlation coefficients

A similar correlation matrix was created for individual scaled scores. As shown in the table below (see also Appendix-1), there was very little correlation between the respondents. The values have correlation coefficients less than 0.4. The dark grey boxes are correlation coefficients greater than 0.4, and the values in light grey boxes are negative correlation coefficients.

	R-01	R-02	R-03	R-04	R-05	R-06	R-07	R-08	R-09	R-10	R-11	R-12	R-13	R-14	R-15	R-16	R-17	R-18	R-19	R-20	R-21	R-22	R-23	R-24	R-25	R-26	R-27	R-28	R-29	R-30	R-31
R-01	100.0%																														
R-02	15.8%	100.0%																													
R-03	8.2%	22.7%	100.0%																												
R-04	12.5%	19.5%	21.8%	100.0%																											
R-05	-1.8%	36.7%	21.9%	17.5%	100.0%																										
R-06	7.6%	27.9%	5.8%	22.1%	22.1%	100.0%																									
R-07	17.8%	16.4%	9.6%	12.3%	20.0%	32.4%	100.0%																								
R-08	14.3%	-1.8%	6.4%	26.9%	1.3%	18.4%	34.9%	100.0%																							
R-09	17.7%	18.3%	7.2%	9.2%	15.5%	10.2%	13.9%	12.9%	100.0%																						
R-10	27.4%	17.5%	23.9%	23.9%	19.3%	13.1%	17.9%	46.9%	12.9%	100.0%																					
R-11	20.0%	32.1%	16.0%	19.1%	29.8%	30.7%	24.3%	22.3%	26.8%	29.3%	100.0%																				
R-12	24.0%	23.8%	13.1%	28.1%	26.6%	28.4%	21.2%	30.8%	25.7%	30.2%	44.4%	100.0%																			
R-13	12.7%	22.7%	5.5%	10.6%	30.4%	28.2%	18.6%	15.3%	3.0%	24.4%	28.7%	36.1%	100.0%																		
R-14	18.1%	27.4%	12.6%	18.0%	23.7%	21.3%	16.8%	26.2%	26.8%	17.1%	48.3%	29.5%	8.6%	100.0%																	
R-15	12.2%	26.7%	15.4%	13.8%	21.4%	18.2%	14.9%	18.8%	32.5%	22.3%	52.3%	28.0%	-0.6%	46.4%	100.0%																
R-16	15.6%	10.1%	10.5%	1.9%	-4.3%	4.9%	25.6%	40.9%	38.1%	26.2%	19.0%	20.4%	-3.2%	18.3%	27.7%	100.0%															
R-17	6.3%	43.6%	10.4%	14.6%	43.1%	23.2%	23.3%	-1.7%	11.4%	18.4%	46.3%	33.8%	48.7%	24.6%	18.2%	-3.6%	100.0%														
R-18	16.4%	13.6%	14.9%	16.4%	14.5%	18.0%	13.5%	49.8%	28.9%	38.8%	43.2%	42.2%	18.3%	45.9%	38.5%	36.6%	27.5%	100.0%													
R-19	5.4%	25.5%	22.4%	21.6%	35.1%	22.4%	24.1%	23.0%	9.4%	36.3%	32.5%	34.5%	38.7%	18.1%	19.1%	9.8%	42.8%	28.6%	100.0%												
R-20	15.2%	15.2%	28.6%	34.5%	20.8%	22.0%	33.8%	50.4%	4.1%	40.8%	25.6%	30.0%	27.9%	18.2%	24.2%	21.2%	26.4%	36.8%	41.4%	100.0%											
R-21	27.0%	30.4%	21.3%	29.9%	21.4%	15.2%	18.5%	30.3%	22.3%	41.2%	32.7%	43.5%	40.5%	25.7%	25.0%	20.7%	34.9%	39.3%	38.5%	43.6%	100.0%										
R-22	13.5%	28.5%	19.2%	22.8%	28.0%	19.5%	13.4%	4.7%	12.7%	27.1%	43.9%	27.7%	4.6%	47.6%	44.6%	0.4%	25.6%	35.9%	19.0%	22.0%	19.6%	100.0%									
R-23	9.0%	29.5%	11.8%	13.0%	23.5%	20.6%	18.0%	13.7%	12.9%	32.1%	42.7%	33.5%	13.9%	30.9%	28.0%	21.1%	34.7%	30.2%	27.0%	22.7%	30.4%	36.9%	100.0%								
R-24	14.8%	15.4%	15.2%	12.8%	8.4%	21.3%	21.1%	53.7%	-2.8%	41.7%	34.4%	30.5%	35.9%	22.4%	22.8%	25.6%	24.6%	40.5%	30.7%	50.7%	35.9%	16.5%	23.1%	100.0%							
R-25	13.2%	27.5%	8.1%	7.5%	17.3%	29.9%	24.9%	23.2%	28.8%	16.8%	47.3%	31.6%	23.9%	41.6%	37.7%	24.2%	36.5%	43.7%	27.6%	23.5%	27.1%	39.2%	32.0%	27.0%	100.0%						
R-26	1.9%	8.4%	9.5%	4.3%	15.3%	27.3%	17.8%	13.7%	-2.0%	7.2%	13.1%	8.5%	-1.4%	14.0%	27.4%	-0.8%	-2.1%	3.0%	13.6%	17.9%	7.6%	20.8%	20.3%	9.5%	18.1%	100.0%					
R-27	12.7%	23.4%	20.2%	27.4%	26.4%	23.8%	39.9%	38.9%	23.9%	45.7%	30.5%	27.6%	14.2%	28.7%	36.6%	33.1%	12.3%	33.3%	36.2%	33.2%	29.2%	19.8%	30.9%	32.5%	32.7%	25.7%	100.0%				
R-28	17.4%	21.1%	17.6%	24.4%	37.8%	27.5%	35.8%	11.1%	16.3%	17.9%	30.3%	31.1%	40.6%	16.0%	11.3%	1.3%	37.3%	14.2%	27.4%	25.7%	24.6%	13.5%	23.9%	6.9%	23.3%	10.6%	27.2%	100.0%			
R-29	29.8%	31.0%	17.3%	33.0%	26.1%	24.9%	34.7%	31.5%	34.1%	39.8%	45.9%	48.2%	33.5%	29.8%	31.6%	30.5%	31.2%	41.5%	39.0%	37.0%	49.4%	24.3%	37.6%	32.3%	28.4%	13.2%	41.0%	39.4%	100.0%		
R-30	15.8%	3.8%	-2.8%	11.0%	1.9%	21.2%	26.1%	57.4%	28.7%	27.1%	44.0%	34.1%	3.6%	44.5%	56.0%	43.4%	3.7%	53.3%	14.2%	23.8%	20.4%	25.4%	21.3%	35.3%	37.6%	12.3%	45.0%	3.4%	27.3%	100.0%	
R-31	8.9%	13.5%	27.4%	26.3%	13.3%	28.7%	33.6%	50.0%	15.4%	28.1%	27.0%	33.7%	18.1%	13.3%	19.4%	25.2%	14.4%	34.6%	29.7%	47.3%	26.9%	4.1%	18.0%	38.7%	25.1%	18.4%	39.7%	25.8%	34.7%	27.0%	100.0%

Exhibit 46 : Matrix showing survey respondents' correlation coefficients

The following correlation scatter plot also demonstrates that each respondent has no significant relationship with the other.

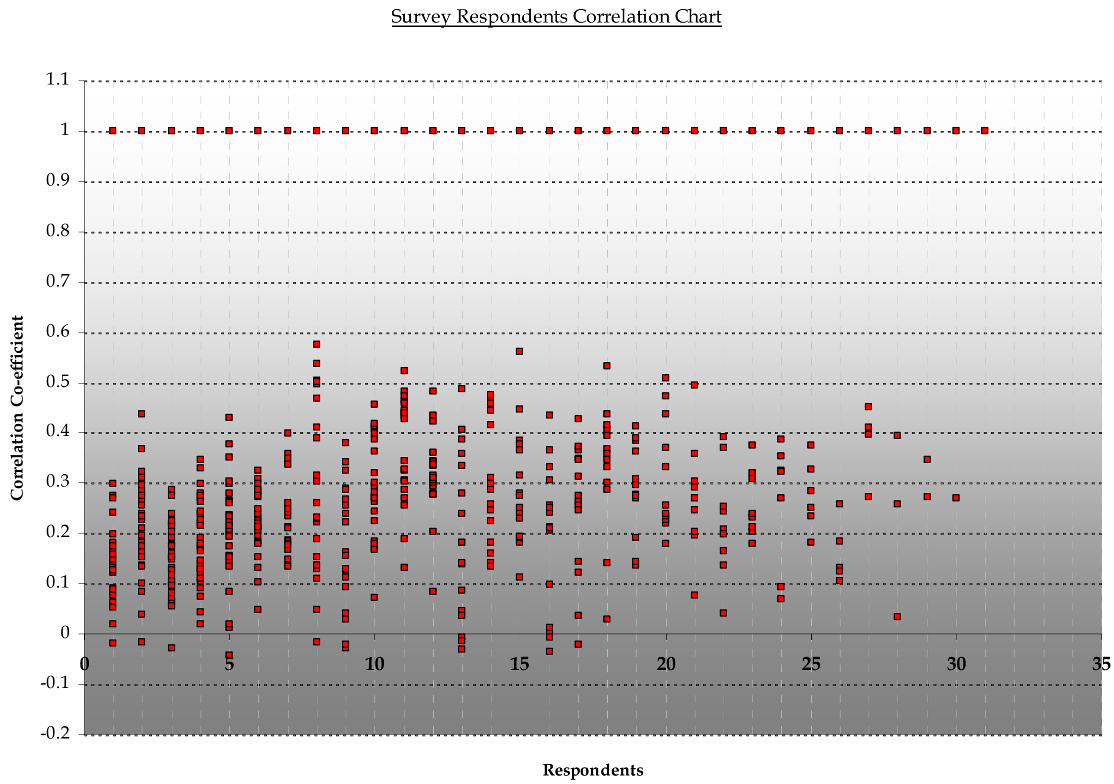

Exhibit 47 : Scatter plot of survey respondents' correlation matrix

Log linear regression using individual scores

The next step was to run individual regressions, with the survey respondents' scaled score as the dependant variable and the market, location, building information as well as building characteristics as independent variables. The first regression equation is as follows:

$$RES\_SC\_Score_n = \alpha + \beta_1 MKT + \beta_2 LOC + \beta_3 BLDG\_INFO + \varepsilon$$

Where $RES\_SC\_Score_n$ is the scaled scores provided by each respondent *n*, MKT is the market attributes, LOC is the location attributes, and BLDG_INFO is the building level information like class, age, etc.

Response Analysis - Building Info, Market, Location using Scaled Scores

	Insignificant	Positive	Negative
_1995 |	54%	18%	29%
_2006 |	46%	32%	21%
class_a |	93%	4%	4%
day_employ~t |	75%	21%	4%
mkt_atlanta |	61%	21%	18%
mkt_boston |	75%	18%	7%
mkt_la |	93%	4%	4%
mkt_oakland |	79%	11%	11%
mkt_orange |	64%	7%	29%
mkt_sacram~o |	79%	4%	18%
mkt_san_de~o |	96%	0%	4%
mkt_san_fr~o |	79%	4%	18%
mkt_san_jose |	86%	0%	14%
mkt_seattle |	68%	4%	29%
noi_sf |	96%	4%	0%
total_sf |	57%	36%	7%

Adjusted R^2	16.60%
R1	5.86%
R2	3.94%
R4	10.10%
R5	15.64%
R6	9.26%
R7	11.79%
R8	44.17%
R9	14.53%
R11	14.01%
R12	13.67%
R13	24.30%
R15	16.75%
R16	18.81%
R17	25.62%
R18	18.06%
R19	17.92%
R20	23.59%
R21	23.46%
R22	17.32%
R23	5.72%
R24	30.95%
R25	18.37%
R26	11.19%
R27	8.36%
R28	18.26%
R29	1.17%
R30	27.12%
R31	14.72%

Note:
The percentages on the second, third and fourth columns are the percentage of respondents who have a insignificant / positive / negative response to the variable (in column 1) based on individual regressions run with each respondent's scaled score.

Exhibit 48 : Summary of survey response analysis – 1

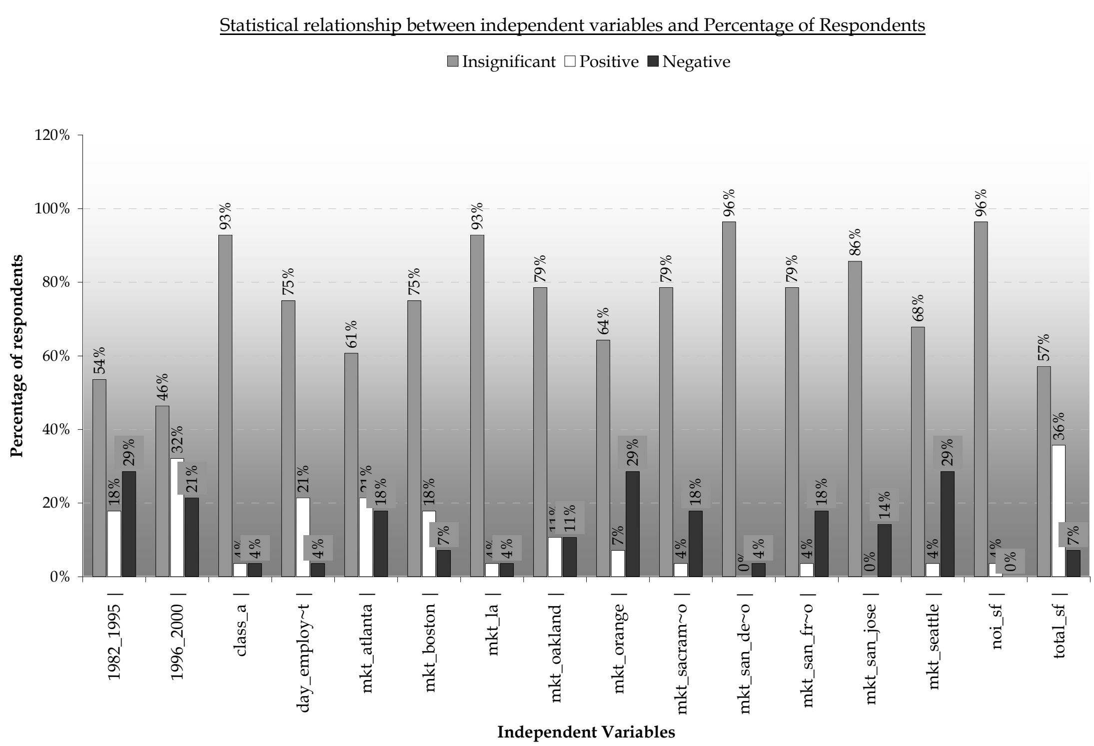

Exhibit 49 : Survey response analysis chart - 1

A large number of variables are insignificant and a number of variables that are significant have a negative relationship with the dependent variable. This noise can be explained in two ways:

i. The design responses were very idiosyncratic and subjective; reinforcing the popular notion that design cannot be evaluated or ranked.

ii. Information (in addition to the single marketing picture) such as floor plans, site plans, site photographs, building facilities may have helped to do a more meaningful ranking of design[39].

Key points to note: when compared to the base case[40],

i. 29% of the respondents scored properties built between 1982 & 1995 lower

ii. 32% of the respondents scored properties built between 1996 & 2000 higher

iii. 18% of the respondents scored properties in Atlanta, while 21% scored Atlanta properties higher.

iv. 29% of the respondents scored properties in East bay/Oakland and Seattle were significantly lower.

v. However, larger buildings (with higher total SF) were scored higher by 36% of the respondents.

vi. Also, there are three respondents (R8, R24, and R30) who have fairly high Adjusted R^2.

The second regression equation that was run is as follows:

$$RES\_SC\_Score_n = \alpha + \beta_1 MKT + \beta_2 LOC + \beta_3 BLDG\_INFO + \beta_4 BLDG\_CHR + \varepsilon$$

[39] The authors acknowledge that while providing additional information about each property would have helped the survey respondents in ranking the buildings with a larger set of design parameters, it would have made the survey as well as research longer. The intent of this research is to be the first brush stroke for what could (and should) be a more exhaustive study.

[40] Here, the base case is a class B (or C) suburban office property in Chicago

Where, in addition to the previous attributes, BLDG_CHR which are objective design attributes (like Window area, floor shape, core location, etc) has been included. The summary of findings is shown below.

Response Analysis - Building Info and Characteristics, Market, Location using Scaled Scores

	Insignificant	Positive	Negative
noi_sf |	100%	0%	0%
day_employ~t |	75%	21%	4%
class_a |	89%	4%	7%
total_sf |	64%	29%	7%
_2006 |	50%	29%	21%
_1995 |	57%	14%	29%
mkt_atlanta |	71%	21%	7%
mkt_boston |	71%	29%	0%
mkt_oakland |	79%	11%	11%
mkt_la |	86%	14%	0%
mkt_orange |	79%	11%	11%
mkt_sacram~o |	89%	4%	7%
mkt_san_de~o |	93%	4%	4%
mkt_san_fr~o |	79%	4%	18%
mkt_san_jose |	89%	4%	7%
mkt_seattle |	75%	4%	21%
taper |	93%	0%	7%
broad_podium |	89%	11%	0%
core_non_ctr |	75%	25%	0%
fl_square |	96%	0%	4%
fl_linear_~r |	89%	0%	11%
fl_curved_~r |	68%	29%	4%
win_0_29 |	86%	0%	14%
win_60_89 |	79%	21%	0%
win_90_100 |	43%	57%	0%
_cons |	0%	100%	0%

Adjusted R^2	20.13%
R1	8.33%
R2	6.10%
R4	10.39%
R5	19.32%
R6	18.09%
R7	18.02%
R8	51.27%
R9	17.44%
R11	17.88%
R12	22.92%
R13	30.44%
R15	24.61%
R16	25.64%
R17	26.08%
R18	20.77%
R19	18.50%
R20	26.08%
R21	23.64%
R22	19.59%
R23	4.32%
R24	32.42%
R25	18.58%
R26	16.56%
R27	11.09%
R28	18.14%
R29	4.55%
R30	33.27%
R31	19.46%

Note:

The percentages on the second, third and fourth columns are the percentage of respondents who have a insignificant / positive / negative response to the variable (in column 1) based on individual regressions run with each respondent's scaled score.

Exhibit 50 : Summary of survey response analysis – 2

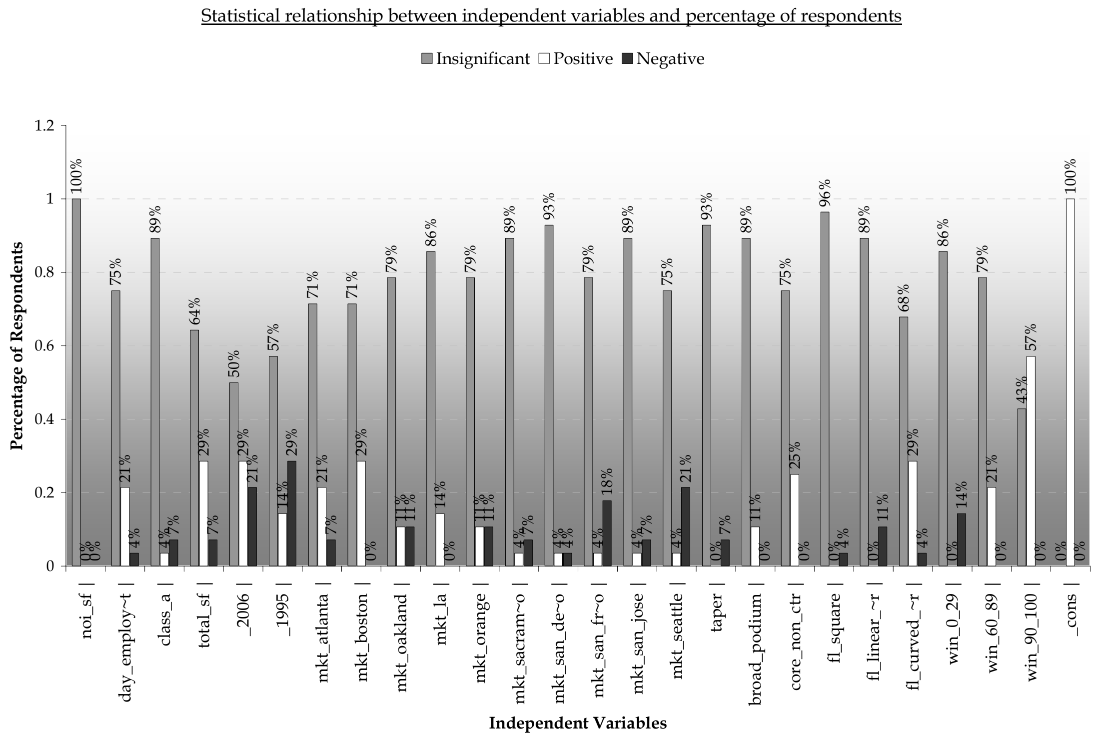

Exhibit 51 : Survey response analysis chart - 2

Here again, a large number of variables are insignificant. When compared to the base case,

i. The first observation is that none of the respondents' score have any relationship to the NOI_SF of the property

ii. 21% of the respondents scored properties within high daytime employment areas higher

iii. 29% scored larger properties higher

iv. 29% of the survey respondents scored properties built between 1996 and 2000 higher. However, 21% of the respondents scored properties built in the same period lower.

v. A significant percentage of respondents scored properties in Boston and Atlanta higher

vi. Interestingly, properties in Seattle and San Francisco have a very significant negative relationship with the respondents score.

vii. Variables like BROAD_PODIUM, TAPER, FL_SQUARE were highly insignificant.

viii. However, design attribute variables like NON_CENTER_CORE, FL_CURVED_IRR, are highly significant at 25% and 29% respectively.

ix. Another important observations if the strong significance of the window-to-wall ratios, demonstrating that respondents ranked building with more glazing/curtain walls higher

x. Here again, the same three respondents (R8, R24 and R30) have fairly high Adjusted R-square values, suggesting a potential sample grouping.

Log linear regressions using sub-groups

An interesting note from the earlier analysis was the isolation of respondent 8, 24 and 30 based on their fairly high Adjusted R-square values. This led to an investigation to see whether the regression results changed if the respondents were grouped and the average scores of the groups were used as the dependent variables. The grouping is made based on the Adjusted R-square values, which in turn reflect fairly well correlated respondents. The first group (group A) has adjusted R-square ranging from 30% and above. Group A contains respondents R8, R24 and R30. Group B (R7, R11-13, R15-22, R31) have adjusted R-square ranging from 20% to 29.99%, and group C (R1-R2, R4-R6, R9, R23, R25-29) have adjusted R-square ranging from 19.99% and below. Using the average scores of these groups, three new variables have been created – AVE_SC_Score_A, AVE_SC_Score_B, and AVE_SC_Score_C.

The first regression equation for group A is as follows:

$$AVE\_SC\_Score\_A = \alpha + \beta_1 MKT + \beta_2 LOC + \beta_3 BLDG\_INFO + \varepsilon$$

. regress ln_group_a noi_sf day_employmentclass_atotal_sf 1996_20001982_1995 mkt_atlan ta mkt_boston mkt_oakland mkt_la mkt_orangemkt_sacramento mkt_san_deigo mkt_san_ francisco mkt_san_josemkt_seattle

Source |	SS	df	MS
Model |	18.6803	16	1.1675
Residual |	18.5086	279	0.0663
Total |	37.1889	295	0.1261

Observations	**296**
F(16, 279)	17.6
Prob F	0
R-squared	0.5023
Adj R-squared	**0.4738**
Root MSE	0.25756

ln_group_a |	Coef.	Std. Err.	t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0020	0.0016	1.2600	0.2100	-0.0011	0.0051
day_employ~t |	0.0000	0.0000	2.2600	0.0250	0.0000	0.0000
class_a |	0.0853	0.0429	1.9900	0.0480	0.0009	0.1698
total_sf |	0.0000	0.0000	7.8100	0.0000	0.0000	0.0000
1996_2000 |	0.2684	0.0566	4.7400	0.0000	0.1569	0.3798
1982_1995 |	0.1127	0.0368	3.0600	0.0020	0.0403	0.1851
mkt_atlanta |	-0.1774	0.0713	-2.4900	0.0130	-0.3178	-0.0370
mkt_boston |	-0.0371	0.0654	-0.5700	0.5710	-0.1659	0.0917
mkt_oakland |	-0.1278	0.0865	-1.4800	0.1410	-0.2980	0.0425
mkt_la |	-0.0742	0.0695	-1.0700	0.2870	-0.2111	0.0626
mkt_orange |	-0.1361	0.0691	-1.9700	0.0500	-0.2722	-0.0001
mkt_sacram~o |	-0.2860	0.1079	-2.6500	0.0080	-0.4984	-0.0736
mkt_san_de~o |	0.1018	0.1048	0.9700	0.3320	-0.1044	0.3080
mkt_san_fr~o |	-0.1374	0.0744	-1.8500	0.0660	-0.2839	0.0091
mkt_san_jose |	-0.2008	0.0715	-2.8100	0.0050	-0.3416	-0.0600
mkt_seattle |	-0.3389	0.0718	-4.7200	0.0000	-0.4802	-0.1975
_cons |	1.3075	0.0695	18.8100	0.0000	1.1707	1.4444

Exhibit 52 : Regression results - Average scaled scores of survey respondents in group A

As shown above, the following behavior can be observed:

i. The Adjusted R-Square is fairly high at 47.4%

ii. The variables such as DAY_EMPLOYMENT, CLASS_A, TOTAL_SF, 1996_2000, 1982_1995 have a positive relationship with the average scaled scores of group A. Properties built between 1996 and 2000 depict a 26% increase in the design ranking by this group, while properties built between 1982 and 1995 show a 11% increase in the design ranking. Class A buildings were also ranked 8.5% higher than the base case properties by this group.

iii. Properties in Atlanta and San Jose were ranked 17% and 20% lower than the base case, and properties in Sacramento and Seattle were also ranked significantly lower (28% and 33% respectively) by this group.

The second regression equation for group B is as follows:

$$AVE\_SC\_Score\_B = \alpha + \beta_1 MKT + \beta_2 LOC + \beta_3 BLDG\_INFO + \varepsilon$$

. regress ln_group_b noi_sf day_employmentclass_atotal_sf 1996_20001982_1995 mkt_atlan ta mkt_boston mkt_oakland mkt_la mkt_orangemkt_sacramento mkt_san_deigo mkt_san_ francisco mkt_san_josemkt_seattle

Source |	SS	df	MS
Model |	3.6599	16	0.2287
Residual |	9.4874	279	0.0340
Total |	13.1473	295	0.0446

Observations	**296**
F(16, 279)	6.73
Prob F	0
R-squared	0.2784
Adj R-squared	**0.237**
Root MSE	0.1844

ln_group_b |	Coef.	Std. Err.	t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0006	0.0011	0.5300	0.6000	-0.0016	0.0028
day_employ~t |	0.0000	0.0000	2.8600	0.0050	0.0000	0.0000
class_a |	-0.0004	0.0307	-0.0100	0.9900	-0.0609	0.0601
total_sf |	0.0000	0.0000	3.0000	0.0030	0.0000	0.0000
1996_2000 |	0.0170	0.0405	0.4200	0.6750	-0.0628	0.0968
1982_1995 |	-0.0461	0.0263	-1.7500	0.0810	-0.0979	0.0057
mkt_atlanta |	0.0823	0.0511	1.6100	0.1080	-0.0183	0.1828
mkt_boston |	0.0153	0.0469	0.3300	0.7450	-0.0770	0.1075
mkt_oakland |	-0.0451	0.0619	-0.7300	0.4670	-0.1670	0.0768
mkt_la |	0.0202	0.0498	0.4100	0.6850	-0.0777	0.1182
mkt_orange |	-0.1057	0.0495	-2.1400	0.0340	-0.2031	-0.0083
mkt_sacram~o |	-0.0884	0.0772	-1.1400	0.2540	-0.2404	0.0637
mkt_san_de~o |	-0.0385	0.0750	-0.5100	0.6090	-0.1861	0.1092
mkt_san_fr~o |	-0.1146	0.0533	-2.1500	0.0320	-0.2195	-0.0098
mkt_san_jose |	-0.0859	0.0512	-1.6800	0.0940	-0.1867	0.0149
mkt_seattle |	-0.1219	0.0514	-2.3700	0.0180	-0.2232	-0.0207
_cons |	1.5181	0.0498	30.5100	0.0000	1.4202	1.6161

Exhibit 53 : Regression results - Average scaled scores of survey respondents in group B

As shown above, the following behavior can be observed:

i. The Adjusted R-Square has decreased to 23.7%, and more number of variables becomes insignificant.

ii. Variables MKT_ORANGE, MKT_SAN_FRANSISCO, and MKT_SEATTLE have negative relationship with the average scaled scores of Group B. The design ranking of the property decreases if the property is in Orange County (10.5%), San Francisco (11.5%), and Seattle (12.1%)

The third regression equation for group C is as follows:

$$AVE\_SC\_Score\_C = \alpha + \beta_1 MKT + \beta_2 LOC + \beta_3 BLDG\_INFO + \varepsilon$$

. regress ln_group_c noi_sf day_employmentclass_atotal_sf 1996_20001982_1995 mkt_atlan ta mkt_boston mkt_oakland mkt_la mkt_orangemkt_sacramento mkt_san_deigo mkt_san_ francisco mkt_san_josemkt_seattle

Source |	SS	df	MS
Model |	0.8328	16	0.0521
Residual |	8.8638	279	0.0318
Total |	9.6967	295	0.0329

Observations	**296**
F(16, 279)	1.64
Prob F	0.0588
R-squared	0.0859
Adj R-squared	**0.0335**
Root MSE	0.17824

ln_group_c |	Coef.	Std. Err.	t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0002	0.0011	0.1600	0.8710	-0.0020	0.0023
day_employ~t |	0.0000	0.0000	0.2200	0.8280	0.0000	0.0000
class_a |	-0.0114	0.0297	-0.3800	0.7010	-0.0699	0.0470
total_sf |	0.0000	0.0000	1.0400	0.3010	0.0000	0.0000
1996_2000 |	0.0000	0.0392	0.0000	1.0000	-0.0771	0.0771
1982_1995 |	-0.0577	0.0255	-2.2600	0.0240	-0.1078	-0.0075
mkt_atlanta |	0.0906	0.0494	1.8300	0.0680	-0.0066	0.1877
mkt_boston |	0.0774	0.0453	1.7100	0.0890	-0.0118	0.1665
mkt_oakland |	0.0995	0.0599	1.6600	0.0970	-0.0183	0.2174
mkt_la |	0.0251	0.0481	0.5200	0.6030	-0.0696	0.1198
mkt_orange |	-0.0059	0.0478	-0.1200	0.9010	-0.1001	0.0882
mkt_sacram~o |	-0.0054	0.0747	-0.0700	0.9420	-0.1524	0.1416
mkt_san_de~o |	0.0356	0.0725	0.4900	0.6240	-0.1071	0.1783
mkt_san_fr~o |	0.0378	0.0515	0.7300	0.4630	-0.0635	0.1392
mkt_san_jose |	0.0001	0.0495	0.0000	0.9990	-0.0973	0.0975
mkt_seattle |	0.0249	0.0497	0.5000	0.6170	-0.0729	0.1227
_cons |	1.5425	0.0481	32.0700	0.0000	1.4478	1.6372

Exhibit 54 : Regression results - Average scaled scores of survey respondents in group C

As shown above, the following behavior can be observed: The Adjusted R-Square has dropped to a low 3.3% and most variables have very little or no relationship with the average scaled scores of group C.

The fourth regression equation for group A is as follows:

$$AVE\_SC\_Score\_A = \alpha + \beta_1 MKT + \beta_2 LOC + \beta_3 BLDG\_INFO + \beta_4 BLDG\_CHR + \varepsilon$$

. regress ln_group_a noi_sf day_employmentclass_atotal_sf 1996_20001982_1995 mkt_atlan ta mkt_boston mkt_oakland mkt_la mkt_orangemkt_sacramento mkt_san_deigo mkt_san_ francisco mkt_san_josemkt_seattletaper broad_podium core_non_ctrfl_squarefl_l inear_irregular fl_curved_irregularwin_0_29 win_60_89 win_90_100

Source |	SS	df	MS
Model |	21.5766	25	0.8631
Residual |	15.6123	270	0.0578
Total |	37.1889	295	0.1261

Observations	**296**
F(25, 270)	14.93
Prob F	0
R-squared	0.5802
Adj R-squared	**0.5413**
Root MSE	0.24046

ln_group_a |	Coef.	Std. Err.	t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0007	0.0016	0.4300	0.6670	-0.0024	0.0037
day_employ~t |	0.0000	0.0000	2.9900	0.0030	0.0000	0.0000
class_a |	0.0660	0.0411	1.6000	0.1100	-0.0150	0.1470
total_sf |	0.0000	0.0000	6.3500	0.0000	0.0000	0.0000
1996_2000 |	0.2116	0.0552	3.8400	0.0000	0.1030	0.3202
1982_1995 |	0.0857	0.0369	2.3200	0.0210	0.0131	0.1583
mkt_atlanta |	-0.1274	0.0720	-1.7700	0.0780	-0.2692	0.0144
mkt_boston |	0.0434	0.0650	0.6700	0.5050	-0.0846	0.1713
mkt_oakland |	-0.1280	0.0846	-1.5100	0.1310	-0.2946	0.0385
mkt_la |	0.0108	0.0696	0.1600	0.8770	-0.1262	0.1479
mkt_orange |	-0.0718	0.0692	-1.0400	0.3000	-0.2080	0.0643
mkt_sacram~o |	-0.1851	0.1040	-1.7800	0.0760	-0.3899	0.0197
mkt_san_de~o |	0.0570	0.1036	0.5500	0.5830	-0.1471	0.2610
mkt_san_fr~o |	-0.1210	0.0713	-1.7000	0.0910	-0.2613	0.0193
mkt_san_jose |	-0.1476	0.0760	-1.9400	0.0530	-0.2973	0.0020
mkt_seattle |	-0.3441	0.0685	-5.0300	0.0000	-0.4789	-0.2093
taper |	-0.0022	0.0406	-0.0500	0.9560	-0.0821	0.0776
broad_podium |	0.0448	0.0549	0.8200	0.4160	-0.0634	0.1529
core_non_ctr |	0.0528	0.0336	1.5700	0.1180	-0.0135	0.1190
fl_square |	-0.0529	0.0552	-0.9600	0.3390	-0.1615	0.0558
fl_linear_~r |	-0.0097	0.0380	-0.2600	0.7980	-0.0845	0.0651
fl_curved_~r |	0.1184	0.0507	2.3400	0.0200	0.0187	0.2182
win_0_29 |	-0.0999	0.0585	-1.7100	0.0890	-0.2150	0.0152
win_60_89 |	0.0864	0.0374	2.3100	0.0220	0.0127	0.1601
win_90_100 |	0.2994	0.0577	5.1900	0.0000	0.1859	0.4129
_cons |	1.2668	0.0760	16.6600	0.0000	1.1171	1.4165

Exhibit 55 : Regression results (incl. design attributes) - Average scaled scores of group A

As shown above, the following behavior can be observed:

i. The Adjusted R-Square is high at 54.1%

ii. As in the previous equations, there is no significant relationship between the score and the NOI_SF

iii. The variables such as DAY_EMPLOYMENT, TOTAL_SF, 1996_2000, 1982_1995 have a positive relationship with the average scaled scores of group A. Properties built between 1996 and 2000 depict a 21% increase in the design ranking by this group, while properties built between 1982 and 1995 show a 8.6% increase in the design ranking.

iv. But importantly, properties with non rectangular floor plans with over 60%-100% glazing on the external wall were scored significantly higher.

The fifth regression equation for group B is as follows:

$$AVE\_SC\_Score\_B = \alpha + \beta_1 MKT + \beta_2 LOC + \beta_3 BLDG\_INFO + \beta_4 BLDG\_CHR + \varepsilon$$

. regress ln_group_b noi_sf day_employmentclass_atotal_sf 1996_20001982_1995 mkt_atlan ta mkt_boston mkt_oakland mkt_la mkt_orangemkt_sacramento mkt_san_deigo mkt_san_ francisco mkt_san_josemkt_seattletaper broad_podium core_non_ctrfl_squarefl_l inear_irregular fl_curved_irregularwin_0_29 win_60_89 win_90_100

Source |	SS	df	MS
Model |	4.7458	25	0.1898
Residual |	8.4015	270	0.0311
Total |	13.1473	295	0.0446

Observations	**296**
F(25, 270)	6.1
Prob F	0
R-squared	0.361
Adj R-squared	**0.3018**
Root MSE	0.1764

ln_group_b |	Coef.	Std. Err.	t	P|t|	[95% Conf.	Interval]
noi_sf |	-0.0004	0.0011	-0.3600	0.7220	-0.0027	0.0018
day_employ~t |	0.0000	0.0000	3.6100	0.0000	0.0000	0.0000
class_a |	-0.0073	0.0302	-0.2400	0.8090	-0.0667	0.0521
total_sf |	0.0000	0.0000	1.9600	0.0510	0.0000	0.0000
1996_2000 |	-0.0087	0.0405	-0.2100	0.8300	-0.0883	0.0710
1982_1995 |	-0.0587	0.0270	-2.1700	0.0310	-0.1119	-0.0054
mkt_atlanta |	0.1354	0.0528	2.5600	0.0110	0.0314	0.2394
mkt_boston |	0.0761	0.0477	1.6000	0.1120	-0.0178	0.1700
mkt_oakland |	-0.0204	0.0620	-0.3300	0.7420	-0.1426	0.1017
mkt_la |	0.0786	0.0511	1.5400	0.1250	-0.0219	0.1791
mkt_orange |	-0.0441	0.0507	-0.8700	0.3860	-0.1439	0.0558
mkt_sacram~o |	-0.0075	0.0763	-0.1000	0.9220	-0.1578	0.1427
mkt_san_de~o |	-0.0512	0.0760	-0.6700	0.5010	-0.2009	0.0984
mkt_san_fr~o |	-0.1035	0.0523	-1.9800	0.0490	-0.2064	-0.0005
mkt_san_jose |	-0.0390	0.0557	-0.7000	0.4850	-0.1488	0.0707
mkt_seattle |	-0.1121	0.0502	-2.2300	0.0270	-0.2110	-0.0132
taper |	-0.0071	0.0297	-0.2400	0.8120	-0.0657	0.0515
broad_podium |	0.0466	0.0403	1.1600	0.2480	-0.0327	0.1260
core_non_ctr |	0.0736	0.0247	2.9800	0.0030	0.0250	0.1222
fl_square |	-0.0252	0.0405	-0.6200	0.5340	-0.1049	0.0545
fl_linear_~r |	-0.0102	0.0279	-0.3700	0.7150	-0.0651	0.0447
fl_curved_~r |	0.0379	0.0372	1.0200	0.3090	-0.0353	0.1111
win_0_29 |	-0.0565	0.0429	-1.3200	0.1880	-0.1410	0.0279
win_60_89 |	0.0625	0.0275	2.2800	0.0240	0.0085	0.1166
win_90_100 |	0.1738	0.0423	4.1100	0.0000	0.0905	0.2570
_cons |	1.4624	0.0558	26.2200	0.0000	1.3526	1.5722

Exhibit 56 : Regression results (incl. design attributes) - Average scaled scores of group B

As shown above, the following behavior can be observed:

i. The Adjusted R-Square has decreased to 30%, and more number of variables becomes insignificant.

ii. As shown before, variables like MKT_SAN_FRANSISCO and MKT_SEATTLE have negative relationship with the average scaled scores of Group B. The design ranking of the property decreases if the property is in San Francisco (10%), and Seattle (11%)

iii. The design ranking of the property decreases if the property was built between 1982 and 1995

iv. The design ranking of properties in Atlanta increased by 13% and properties with non center core increased by 7%.

v. And here again, the Window proportion variables have a highly significant positive relationship to design score of this group

The sixth and final regression equation for group C is as follows:

$$AVE\_SC\_Score\_C = \alpha + \beta_1 MKT + \beta_2 LOC + \beta_3 BLDG\_INFO + \beta_4 BLDG\_CHR + \varepsilon$$

As before, the following behavior was be observed:

i. The Adjusted R-Square is has decreased to 11%, and all but a few variables become insignificant.

ii. Atlanta, Boston and East bay/Oakland have a positive relationship to the scores from this group, as do the podium and core location variables. Here again, the window proportion variables are significant

Observations

The first level analysis of the average scores across MSAs, Building Classes and Heights yielded very little insight with regards to the design ranking of the buildings across these categories. The "two-camp" notion was investigated and dismissed after creating a correlation matrix. The matrix confirmed the suspicion that design ranking was highly subjective since very few respondents had a significant positive correlation with each other. The third level analysis was conducted to identify variables that have a positive relationship with the individual scores. Age, building SF, design attributes like core locations, floor shape and window proportions exhibited a positive relationship, while several markets like San Francisco and Seattle exhibited a significantly negative relationship. The final step was to group the survey respondents, based on their adjusted R-square values, and then run regression to see the relationship to NOI_SF and objective design attributes. Average scaled scores by Group A (with high correlations and adjusted R-square values) demonstrated a positive relationship with location attribute (day time employment), building age, building SF, core location (non center), larger window proportions (window to wall ratio of over 60%). Group B and C (with lower correlations and adjusted R-square values) demonstrated a positive relationship with location attribute (day time employment), building SF, core location (non center), larger window proportions (window to wall ratio of +60%).

In summary, the two main points stemming from the analysis in this chapter are as follows:

i. Although the scores given by the survey respondents for properties were not highly correlated, design ranking for properties increased, to a certain degree, for properties with non rectangular floor plans with non-center cores and higher window to wall proportions.

ii. The survey results illustrate that the NOI_SF possess little explanatory powers in respondent's average scaled scores based on the sample size of 296 observations. In other words, an office building's potential to generate income seems to have little correlation to how younger architects perceive good design/architecture.

CHAPTER VI: DOES DESIGN IMPACT NOI?

Log linear regression results

This section presents the results of the regression runs using 296 observations with NOI per SF as the dependent variables using the following equation:

$$NOI\_SF\_LOG = \alpha + \beta_1 MKT + \beta_2 LOC + \beta_3 BLDG\_INFO + AVE\_SCALED + \varepsilon$$

Where NOI_SF_LOG is the natural log of the average NOI of a property from 2000-2005, MKT_ are the market attributes, LOC are the location attributes, and BLDG_INFO are Class, age, etc. and AVE_SCALED representing the average scaled survey ranking for each observation . A summary of the findings are shown below:

Source |	SS	df	MS
Model |	22.1977	25	0.8879
Residual |	28.2304	270	0.1046
Total |	50.4281	295	0.1709

Number of obs	**296**
F(25, 270)	8.49
Prob > F	0
R-squared	0.4402
Adj R-squared	**0.3884**
Root MSE	0.32335

noi_sf_log |	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
day_employ~t |	0.0000	0.0000	2.8400	0.0050	0.0000	0.0000
class_a |	0.0857	0.0552	1.5500	0.1220	-0.0230	0.1945
total_sf |	0.0000	0.0000	1.6100	0.1090	0.0000	0.0000
_2000 |	0.0941	0.0741	1.2700	0.2050	-0.0517	0.2399
_1995 |	-0.0500	0.0498	-1.0000	0.3160	-0.1480	0.0480
mkt_atlanta |	-0.0251	0.0976	-0.2600	0.7980	-0.2172	0.1671
mkt_boston |	0.3854	0.0859	4.4900	0.0000	0.2164	0.5545
mkt_oakland |	0.1914	0.1132	1.6900	0.0920	-0.0314	0.4143
mkt_la |	0.4207	0.0909	4.6300	0.0000	0.2418	0.5997
mkt_orange |	0.1527	0.0924	1.6500	0.0990	-0.0291	0.3346
mkt_sacram~o |	0.0608	0.1398	0.4300	0.6640	-0.2145	0.3360
mkt_san_de~o |	0.2115	0.1388	1.5200	0.1290	-0.0618	0.4847
mkt_san_fr~o |	0.5727	0.0907	6.3200	0.0000	0.3942	0.7513
mkt_san_jose |	0.6390	0.0940	6.8000	0.0000	0.4539	0.8242
mkt_seattle |	0.1524	0.0917	1.6600	0.0980	-0.0282	0.3329
taper |	-0.0131	0.0545	-0.2400	0.8110	-0.1205	0.0943
broad_podium |	-0.0599	0.0740	-0.8100	0.4200	-0.2056	0.0859
core_non_ctr |	0.0791	0.0457	1.7300	0.0850	-0.0109	0.1691
fl_square |	-0.0934	0.0742	-1.2600	0.2090	-0.2394	0.0526
fl_linear_~r |	0.1179	0.0505	2.3300	0.0200	0.0184	0.2173
fl_curved_~r |	0.1327	0.0682	1.9400	0.0530	-0.0016	0.2671
win_0_29 |	-0.0974	0.0786	-1.2400	0.2160	-0.2522	0.0574
win_60_89 |	0.1072	0.0501	2.1400	0.0330	0.0085	0.2058
win_90_100 |	0.1027	0.0801	1.2800	0.2010	-0.0551	0.2604
ave_scaled |	-0.0271	0.0266	-1.0200	0.3090	-0.0794	0.0253
_cons |	2.5918	0.1499	17.2900	0.0000	2.2966	2.8870

Exhibit 57 : Regression results for Model 2

The adjusted R-Squared value of this model is 38.9%. Other permutations of this regression produced adjusted R-Squared between 39%-41.9% and are attached in the appendix for review. The dummy variables used in this model are: Non Class A, Age of Pre-1982, Chicago MSA, Non-Taper, Non-Podium, Core Center, Rectangular Floor Plate and 30-59% Windows.

The intercept or base case of the regression model presents a $13.35 NOI per SF of (2.591807 *Exponent* Natural Log = $13.35).

The positive coefficient for average daytime employment at a one mile radius from the observation indicates that there is a small NOI per SF premium for each increase in daytime employees. For example, the percentage difference in NOI per SF when comparing an observation with 1,000 employees vs. 300,000 employees is (0.000000779 x 290,000 = 0.22591). The premium paid by tenants to locate in high daytime employment location is $1.25 NOI per SF (0.22591 *Exponentiation* Natural Log = $1.25).

While the Class_A coefficient is positive, it does exhibit a large 12.2% significance or t-statistic of 1.55. Given the relatively small number of observations, a +/- 10% significance or +/- 1.6 t–statistic will be used to measure if a variable can be considered significantly different from 0. In this instance, a building which as been classified as Class A enjoys an 8.6% increase in NOI per SF or $1.09 (.0857229 *Exponent* Natural Log = $1.09) over non Class A buildings.

Total SF is the second variables which resulted in a borderline significance value of 10.9% or t-statistic of 1.61. If the positive coefficient for this variable is considered statistically significant, an increase in a properties total rentable SF increases it ability to general NOI per SF. For example, the difference in NOI per SF between a 20,000 SF property and 1,000,000 SF property, holding all other variables constant is $1.21 NOI per SF (0.000000197 x 980,000 = 0.22591, 0.22591 *Exponent* Natural Log = $1. 21) vs. the base case intercept value of $13.35 NOI per SF.

Even though the dummy Age variables exhibit statistically insignificant coefficients, the positive sign for the observations brought to the market from 1996-2000 are positive in relationship to the pre-1982 age dummy. The coefficient for the age dummy from 1982-1996 is negative and could be attributed to the small sample size.

Properties which have been classified as Taper and/or Broad Podium are not significantly different from the base case dummy variable. Given the small number of taper and broad podium observations spread over 11 MSA's, these finding are not surprising. In addition, there are no clear expectations from real estate professionals that buildings possessing these two physical building characteristics can generate higher operating income. Often, the intent of tapered properties is to maximize the income generating capability of a property my enlarging top floor rentable spaces while imparting a different architectural look to the property. Likewise, a broad podium is typically unitized not because this building configuration type can generate more income for typical office floors.

The positive coefficient for Core Non Center is statistically significant with a t-statistic of 1.73 or significance of 8.5% in relationship to the Core Center base case dummy variable. The .0790959 coefficient translates into an increase of $1.08 NOI per SF (.0790959 *Exponent* Natural Log = $1.08).

The Square Floor Plate coefficient is negative. Even though this coefficient results in a significance of 20.9%, the negative sign of the coefficient corresponds to the base case Rectangular Floor Plan dummy variable.

Both the Linear Irregular and Curved Irregular Floor Plate designations have produced statistically significant results. With a significance of 2% and 5.3%, both characteristics exhibit strong positive correlations in the range of 11.7-13.2%. When translated into NOI per SF, these properties command a premium of $1.13-1.14 NOI per SF over the base case Rectangular Floor Plate (0.1178622 *Exponent* Natural Log = $1.13, 0.1327401 *Exponent* Natural Log = $1.14). Furthermore, the confidence intervals of these 2 variables largely overlap. This shows that, while these floor shapes are significant, they cannot be distinguished from each other.

Windows 0-29% displays a statistically insignificant coefficient of -9.7%. This value confirms the generally accepted thought that buildings with less exterior windows draw in less daylight and generate income at a discount, when compared to base case.

The positive coefficient of 0.1071578 for Window 60-89% is statistically significant with a t-statistic of 2.14 and a significance of 3.3%. Following the previously discussed relationship between exterior windows and income, the 10.7% increase in NOI per SF against the base case confirms that buildings with more windows (and consequently, more daylight) generate more income. Properties falling into the category Windows 60-89% result in an additional $1.11 NOI per SF (0.1071578 *Exponent* Natural Log = $1.11).

While the coefficient Window 90-100% is not statistically significant, the positive sign of the variable is encouraging. Only 27 properties within the larger data set fell into the Window 90-100% variable and thus, leading to significance of 20.1%.

The last finding of this regression concerns the variable AVE_SCALED. Representing the average scaled scores for the 296 properties, this metric has little explanatory power. Consisting of a t-statistic of -1.02 and Significance of 30.9%, this variable is statistically no different that 0. While of little statistical use, it is should be noted that the coefficient for AVE_SCALED is negative. This could suggest that properties which scored lower on the subjective survey actually generated higher average NOI per SF from 2000-2005.

The results demonstrate that, within the scope of this research and the existing sample size of 296 observations spread over 11 US MSA's, a plain vanilla rectangular office building with a centrally located core generates lower NOI per SF in comparison to irregularly shaped office buildings with non central cores.

Summary of results

Following is a bullet point summary of the log linear regression results using Average NOI per SF as the dependent variable:

i. The higher the average daytime employment at a one mile radius from each observation, the higher the average NOI per SF the property can command.

ii. Similarly, it was found that a building, classified as Class A, has an upward premium associated with them. However, the results of the regression illustrate that this finding may not be statistically significant. Further study is needed to determine the role of a Class A designation on a property.

iii. Taking into account the small number of observations, Building SF is another observation that proves difficult to interpret. Either this variable is not significant or properties with higher total rentable SF on average command higher NOI per SF.

iv. A building with a core which is not located in the center of the floor plan generates higher premium. This finding can be also associated with significant premium the market paid for non-rectangular and non-square building shapes. Typically, uniquely shaped buildings often have non-central cores and the combination of the 2 building characteristics generates double digit increases in average NOI per SF.

v. Within the limits of the data set, properties with more windows also generate double digit increases in average NOI per SF.

vi. The average scaled survey results were not statistically significant. In other words, the architect's rankings were not related to the average NOI per SF generated by the office building within the data set. Finally, a negative coefficient suggests that properties that were ranked lower by architects generated higher average NOI per SF.

CHAPTER VII: CONCLUSIONS

This empirical study explores the impact of "good" design on office building NOI per SF and utilizes a data set consisting of 296 buildings located in the US. These buildings are located in Atlanta, Boston, Chicago, East Bay/ Oakland, Los Angeles, Orange County, San Francisco, Sa Diego, San Jose, Sacramento, and Seattle.

This study attempted to capture the design ranking of buildings in the data set using an online survey completed by 31 young architects. The results of the survey showed zero correlation between the respondents' design ranking scores. This zero results imply that, by asking architects to rank the design quality of buildings based on one marketing photograph, it cannot be determined whether the building is well designed or not. In addition, the zero results statistically show that architectural/design preferences (in other words – taste) are in fact idiosyncratic. This reinforces the need to identify and use specific design attributes, which constitute good office building design, as followed by earlier researches like Vandell and Lane (1989), Hough and Kratz (1983), Doiron et al. (1992).

This study captures four unique quantifiable office building design attributes like floor shapes, presence of podium, tapering of building mass, and amount of windows in exterior walls. In addition to structural and location variables, the average scaled score for each building was then included as independent variable. Some of the attributes were discarded due to the lack of theoretical justification, explanatory impact or lack of sufficient data. With net operating income as the dependent variable, log linear regressions were run to evaluate the impact of design on office building net operating income.

It was found that certain building design attributes like floor shape and amount of windows on exterior walls have a positive impact on office net operating income. This result suggests that buildings that are non rectangular or square in plan, but have linear irregular or curved irregular floor plans generate almost 11%-13% more income. It also showed that buildings with 60% - 90% windows on the external walls increased net operating income by 10.7%.

In conclusion, this study reveals that office tenants are willing to pay a premium for buildings that are unlike the typical cereal box office building or that the operating costs is lowers for such buildings, or both. The model shows a clear relationship between certain design attributes and office net operating income.

Recommendations for further study: Quantitative

Further research can focus on several empirical questions. This research provides a foundation that can be used to analyze the value of "good" design with additional controls for operating costs, real estate taxes, and total development costs. This would help answer the question "Does good design increase profitability, and if so, how much?"

The objective design attributes like floor shape and percentage of windows offer some real potential to explore and determine the impact of these attributes on office rents. Objective design metrics like day-light factors can be quantified accurately through another survey completed by property managers or project managers/architects. Additional quantitative building characteristics such as construction materials (steel or concrete), column spacing, maximum electrical loads per sf, floor to floor heights, maximum floor loading per SF, core factor (percentage of total gross SF per floor which is designated to the core), floor plate efficiency (Net Rentable SF/Gross SF), number of loading docks, level of security, operating hours for tenant access, size and volume of lobby, distance to public transportations, number/ ability of individual office workers to control micro-climates, distance to major highways, distance to airports, landscaping, other on-site amenities such as retail and/or fitness center, drop off / turn around for visitors and in the future, if building is LEED certified. The impact of these metrics can be analyzed on both the NOI as well as the operating and development costs of the property. A proxy for calculating the daylight factor could be using values generated by dividing the circumference of building by rentable sf per floor.

Another research idea that can build on the current research is to evaluate if and how much more does an expensive (in terms of per square foot development costs) building generate in rents when compared to a regular building. This can explored by controlling for total development costs of each property vs. asking or gross rents.

And more importantly, the immediate next step extending from this research would be to include lease level analysis. Questions determining which type of tenants have a tendency to pay for good design, does lease length impact how much the tenants are willing to pay for good design, etc.

Recommendations for further study: Subjective

In terms of subjective design metrics, as mentioned before, additional photographs of properties (at a minimum two exterior and two interior - lobby and typical office), aerial site photograph, site plan (with landscaping and parking plans), typical building floor plan, and information regarding use of materials and fixtures would greater help architects to evaluate design better. Also, a survey completed by a larger sample of architects based on diverse professional experience and educational history may generate a more robust design preference pattern. Finally, this research can be extended to not only identify what is "good" design as perceived by architects, but also by tenants, developers, and space users.

APPENDIX

Exhibit A - Correlation matrix for survey respondents

	R-01	R-02	R-03	R-04	R-05	R-06	R-07	R-08	R-09	R-10	R-11	R-12	R-13	R-14	R-15	R-16	R-17	R-18	R-19	R-20	R-21	R-22	R-23	R-24	R-25	R-26	R-27	R-28	R-29	R-30	R-31
R-01	100.0%																														
R-02	15.8%	100.0%																													
R-03	8.2%	22.7%	100.0%																												
R-04	12.5%	19.5%	21.8%	100.0%																											
R-05	-1.8%	36.7%	21.9%	17.5%	100.0%																										
R-06	7.6%	27.9%	5.8%	22.1%	22.1%	100.0%																									
R-07	17.8%	16.4%	9.6%	12.3%	20.0%	32.4%	100.0%																								
R-08	14.3%	-1.8%	6.4%	26.9%	1.3%	18.4%	34.9%	100.0%																							
R-09	17.7%	18.3%	7.2%	9.2%	15.5%	10.2%	13.9%	12.9%	100.0%																						
R-10	27.4%	17.5%	23.9%	23.9%	19.3%	13.1%	17.9%	46.9%	12.9%	100.0%																					
R-11	20.0%	32.1%	16.0%	19.1%	29.8%	30.7%	24.3%	22.3%	26.8%	29.3%	100.0%																				
R-12	24.0%	23.8%	13.1%	28.1%	26.6%	28.4%	21.2%	30.8%	25.7%	30.2%	44.4%	100.0%																			
R-13	12.7%	22.7%	5.5%	10.6%	30.4%	28.2%	18.6%	15.3%	3.0%	24.4%	28.7%	36.1%	100.0%																		
R-14	18.1%	27.4%	12.6%	18.0%	23.7%	21.3%	16.8%	26.2%	26.8%	17.1%	48.3%	29.5%	8.6%	100.0%																	
R-15	12.2%	26.7%	15.4%	13.8%	21.4%	18.2%	14.9%	18.8%	32.5%	22.3%	52.3%	28.0%	-0.6%	46.4%	100.0%																
R-16	15.6%	10.1%	10.5%	1.9%	-4.3%	4.9%	25.6%	40.9%	38.1%	26.2%	19.0%	20.4%	-3.2%	18.3%	27.7%	100.0%															
R-17	6.3%	43.6%	10.4%	14.6%	43.1%	23.2%	23.3%	-1.7%	11.4%	18.4%	46.3%	33.8%	48.7%	24.6%	18.2%	-3.6%	100.0%														
R-18	16.4%	13.6%	14.9%	16.4%	14.5%	18.0%	13.5%	49.8%	28.9%	38.8%	43.2%	42.2%	18.3%	45.9%	38.5%	36.6%	27.5%	100.0%													
R-19	5.4%	25.5%	22.4%	21.6%	35.1%	22.4%	24.1%	23.0%	9.4%	36.3%	32.5%	34.5%	38.7%	18.1%	19.1%	9.8%	42.8%	28.6%	100.0%												
R-20	15.2%	15.2%	28.6%	34.5%	20.8%	22.0%	33.8%	50.4%	4.1%	40.8%	25.6%	30.0%	27.9%	18.2%	24.2%	21.2%	26.4%	36.8%	41.4%	100.0%											
R-21	27.0%	30.4%	21.3%	29.9%	21.4%	15.2%	18.5%	30.3%	22.3%	41.2%	32.7%	43.5%	40.5%	25.7%	25.0%	20.7%	34.9%	39.3%	38.5%	43.6%	100.0%										
R-22	13.5%	28.5%	19.2%	22.8%	28.0%	19.5%	13.4%	4.7%	12.7%	27.1%	43.9%	27.7%	4.6%	47.6%	44.6%	0.4%	25.6%	35.9%	19.0%	22.0%	19.6%	100.0%									
R-23	9.0%	29.5%	11.8%	13.0%	23.5%	20.6%	18.0%	13.7%	12.9%	32.1%	42.7%	33.5%	13.9%	30.9%	28.0%	21.1%	34.7%	30.2%	27.0%	22.7%	30.4%	36.9%	100.0%								
R-24	14.8%	15.4%	15.2%	12.8%	8.4%	21.3%	21.1%	53.7%	-2.8%	41.7%	34.4%	30.5%	35.9%	22.4%	22.8%	25.6%	24.6%	40.5%	30.7%	50.7%	35.9%	16.5%	23.1%	100.0%							
R-25	13.2%	27.5%	8.1%	7.5%	17.3%	29.9%	24.9%	23.2%	28.8%	16.8%	47.3%	31.6%	23.9%	41.6%	37.7%	24.2%	36.5%	43.7%	27.6%	23.5%	27.1%	39.2%	32.0%	27.0%	100.0%						
R-26	1.9%	8.4%	9.5%	4.3%	15.3%	27.3%	17.8%	13.7%	-2.0%	7.2%	13.1%	8.5%	-1.4%	14.0%	27.4%	-0.8%	-2.1%	3.0%	13.6%	17.9%	7.6%	20.8%	20.3%	9.5%	18.1%	100.0%					
R-27	12.7%	23.4%	20.2%	27.4%	26.4%	23.8%	39.9%	38.9%	23.9%	45.7%	30.5%	27.6%	14.2%	28.7%	36.6%	33.1%	12.3%	33.3%	36.2%	33.2%	29.2%	19.8%	30.9%	32.5%	32.7%	25.7%	100.0%				
R-28	17.4%	21.1%	17.6%	24.4%	37.8%	27.5%	35.8%	11.1%	16.3%	17.9%	30.3%	31.1%	40.6%	16.0%	11.3%	1.3%	37.3%	14.2%	27.4%	25.7%	24.6%	13.5%	23.9%	6.9%	23.3%	10.6%	27.2%	100.0%			
R-29	29.8%	31.0%	17.3%	33.0%	26.1%	24.9%	34.7%	31.5%	34.1%	39.8%	45.9%	48.2%	33.5%	29.8%	31.6%	30.5%	31.2%	41.5%	39.0%	37.0%	49.4%	24.3%	37.6%	32.3%	28.4%	13.2%	41.0%	39.4%	100.0%		
R-30	15.8%	3.8%	-2.8%	11.0%	1.9%	21.2%	26.1%	57.4%	28.7%	27.1%	44.0%	34.1%	3.6%	44.5%	56.0%	43.4%	3.7%	53.3%	14.2%	23.8%	20.4%	25.4%	21.3%	35.3%	37.6%	12.3%	45.0%	3.4%	27.3%	100.0%	
R-31	8.9%	13.5%	27.4%	26.3%	13.3%	28.7%	33.6%	50.0%	15.4%	28.1%	27.0%	33.7%	18.1%	13.3%	19.4%	25.2%	14.4%	34.6%	29.7%	47.3%	26.9%	4.1%	18.0%	38.7%	25.1%	18.4%	39.7%	25.8%	34.7%	27.0%	100.0%

Exhibit B – NOI_SF as dependent variable: Model 1

NOI per SF as dependent variable (deleted 6 observations with NOI over $60/sf)

Source |	SS	df	MS			
Model |	18.6348	25	0.7454			
Residual |	21.2462	264	0.0848			
Total |	39.8810	289	0.1380			

Number of obs	**290**
F(25, 264)	9.26
Prob > F	0
R-squared	0.4673
Adj R-squared	**0.4168**
Root MSE	0.28369

noi_sf_log |	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
day_employ~t |	0.0000	0.0000	2.0900	0.0380	0.0000	0.0000
class_a |	0.1348	0.0491	2.7400	0.0060	0.0381	0.2315
total_sf |	0.0000	0.0000	2.3600	0.0190	0.0000	0.0000
_2000 |	0.0661	0.0657	1.0100	0.3150	-0.0633	0.1956
_1995 |	-0.1065	0.0442	-2.4100	0.0170	-0.1935	-0.0196
mkt_atlanta |	-0.1245	0.0864	-1.4400	0.1510	-0.2946	0.0457
mkt_boston |	0.3033	0.0765	3.9600	0.0000	0.1526	0.4540
mkt_oakland |	0.1076	0.0998	1.0800	0.2820	-0.0889	0.3042
mkt_la |	0.2944	0.0811	3.6300	0.0000	0.1347	0.4540
mkt_orange |	0.0945	0.0814	1.1600	0.2470	-0.0658	0.2549
mkt_sacram~o |	-0.0142	0.1234	-0.1100	0.9090	-0.2571	0.2287
mkt_san_de~o |	0.1463	0.1221	1.2000	0.2320	-0.0940	0.3867
mkt_san_fr~o |	0.5184	0.0801	6.4700	0.0000	0.3606	0.6761
mkt_san_jose |	0.4559	0.0856	5.3300	0.0000	0.2875	0.6244
mkt_seattle |	0.1164	0.0806	1.4400	0.1500	-0.0423	0.2751
taper |	0.0076	0.0480	0.1600	0.8740	-0.0868	0.1021
broad_podium |	-0.0302	0.0650	-0.4600	0.6420	-0.1583	0.0978
core_non_ctr |	0.0078	0.0409	0.1900	0.8500	-0.0728	0.0883
fl_square |	-0.0477	0.0654	-0.7300	0.4670	-0.1765	0.0811
fl_linear_~r |	0.0695	0.0447	1.5600	0.1210	-0.0184	0.1575
fl_curved_~r |	0.1733	0.0601	2.8800	0.0040	0.0550	0.2916
win_0_29 |	-0.1009	0.0692	-1.4600	0.1460	-0.2371	0.0353
win_60_89 |	0.0383	0.0452	0.8500	0.3980	-0.0507	0.1273
win_90_100 |	0.0579	0.0708	0.8200	0.4140	-0.0814	0.1973
ave_scaled |	-0.0280	0.0234	-1.1900	0.2330	-0.0741	0.0181
_cons |	2.7116	0.1326	20.4500	0.0000	2.4506	2.9727

Exhibit C – NOI_SF as dependent variable: Model 2

NOI per SF as dependent variable (deleted 10 observations with NOI over $46/sf)

Source |	SS	df	MS
Model |	17.1074	25	0.6843
Residual |	19.2952	260	0.0742
Total |	36.4026	285	0.1277

Number of obs	**286**
F(25, 260)	9.22
Prob > F	0
R-squared	0.4699
Adj R-squared	**0.419**
Root MSE	0.27242

noi_sf_log |	Coef.	Std. Err	. t	P>|t|	[95% Conf.	Interval]
day_employ~t |	0.0000	0.0000	2.1600	0.0320	0.0000	0.0000
class_a |	0.1288	0.0477	2.7000	0.0070	0.0348	0.2228
total_sf |	0.0000	0.0000	2.5800	0.0100	0.0000	0.0000
_2000 |	0.1103	0.0638	1.7300	0.0850	-0.0153	0.2359
_1995 |	-0.0671	0.0432	-1.5500	0.1220	-0.1522	0.0180
mkt_atlanta |	-0.1220	0.0830	-1.4700	0.1430	-0.2855	0.0415
mkt_boston |	0.3106	0.0735	4.2200	0.0000	0.1658	0.4554
mkt_oakland |	0.0929	0.0959	0.9700	0.3340	-0.0960	0.2818
mkt_la |	0.2834	0.0779	3.6400	0.0000	0.1300	0.4368
mkt_orange |	0.0914	0.0783	1.1700	0.2440	-0.0627	0.2456
mkt_sacram~o |	-0.0223	0.1185	-0.1900	0.8510	-0.2556	0.2110
mkt_san_de~o |	0.1193	0.1176	1.0100	0.3110	-0.1122	0.3509
mkt_san_fr~o |	0.4730	0.0781	6.0500	0.0000	0.3191	0.6269
mkt_san_jose |	0.4088	0.0833	4.9100	0.0000	0.2447	0.5729
mkt_seattle |	0.1165	0.0774	1.5100	0.1340	-0.0359	0.2690
taper |	0.0150	0.0461	0.3200	0.7460	-0.0759	0.1058
broad_podium |	-0.0129	0.0625	-0.2100	0.8370	-0.1360	0.1103
core_non_ctr |	0.0212	0.0397	0.5400	0.5930	-0.0569	0.0994
fl_square |	-0.0560	0.0634	-0.8800	0.3780	-0.1809	0.0689
fl_linear_~r |	0.0349	0.0436	0.8000	0.4240	-0.0510	0.1207
fl_curved_~r |	0.1658	0.0578	2.8700	0.0040	0.0521	0.2796
win_0_29 |	-0.0973	0.0664	-1.4700	0.1440	-0.2281	0.0335
win_60_89 |	0.0164	0.0438	0.3800	0.7080	-0.0698	0.1026
win_90_100 |	0.0502	0.0680	0.7400	0.4610	-0.0838	0.1842
ave_scaled |	-0.0262	0.0225	-1.1600	0.2460	-0.0706	0.0181
_cons |	2.7027	0.1275	21.2000	0.0000	2.4517	2.9537

Exhibit D – NOI_SF as dependent variable: Model 2

NOI per SF as dependent variable (deleted 9 observations located in Sacramento)

Source |	SS	df	MS		
				Number of obs =	**287**
				F(24, 262)	8.61
Model |	21.9939	24	0.9164	Prob > F	0
Residual |	27.8995	262	0.1649	R-squared	0.4408
				Adj R-squared	**0.3896**
Total |	49.8934	286	0.1745	Root MSE	0.32632

noi_sf_log |	Coef.	Std. Err	. t	P>|t|	[95% Conf.	Interval]
day_employ~t |	0.0000	0.0000	2.8100	0.0050	0.0000	0.0000
class_a |	0.0854	0.0558	1.5300	0.1270	-0.0244	0.1952
total_sf |	0.0000	0.0000	1.6000	0.1100	0.0000	0.0000
_2000 |	0.0893	0.0769	1.1600	0.2470	-0.0621	0.2406
_1995 |	-0.0527	0.0504	-1.0500	0.2970	-0.1520	0.0465
mkt_atlanta |	-0.0202	0.0987	-0.2000	0.8380	-0.2145	0.1742
mkt_boston |	0.3875	0.0869	4.4600	0.0000	0.2165	0.5586
mkt_oakland |	0.1945	0.1144	1.7000	0.0900	-0.0308	0.4199
mkt_la |	0.4245	0.0919	4.6200	0.0000	0.2435	0.6054
mkt_orange |	0.1536	0.0934	1.6400	0.1010	-0.0303	0.3375
mkt_san_de~o |	0.2170	0.1405	1.5400	0.1240	-0.0597	0.4936
mkt_san_fr~o |	0.5734	0.0916	6.2600	0.0000	0.3930	0.7538
mkt_san_jose |	0.6410	0.0951	6.7400	0.0000	0.4538	0.8282
mkt_seattle |	0.1528	0.0926	1.6500	0.1000	-0.0295	0.3352
taper |	-0.0039	0.0556	-0.0700	0.9450	-0.1133	0.1056
broad_podium |	-0.0641	0.0748	-0.8600	0.3920	-0.2114	0.0832
core_non_ctr |	0.0808	0.0466	1.7400	0.0840	-0.0109	0.1725
fl_square |	-0.0884	0.0750	-1.1800	0.2390	-0.2361	0.0593
fl_linear_~r |	0.1262	0.0519	2.4300	0.0160	0.0241	0.2284
fl_curved_~r |	0.1369	0.0701	1.9500	0.0520	-0.0010	0.2749
win_0_29 |	-0.0952	0.0795	-1.2000	0.2320	-0.2518	0.0614
win_60_89 |	0.1126	0.0518	2.1700	0.0310	0.0106	0.2146
win_90_100 |	0.1058	0.0812	1.3000	0.1940	-0.0542	0.2658
ave_scaled |	-0.0302	0.0272	-1.1100	0.2670	-0.0837	0.0233
_cons |	2.5968	0.1519	17.0900	0.0000	2.2976	2.8959

Exhibit E - Regression results for each survey respondent

Dependant variable – Respondent 1

. regress ln_r1 noi_sf day_employment class_a total_sf _1996_2000 _1982_1995 mkt_atlantamkt _boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_franci sco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	20.39	16	10.27
Residual |	165.58	279	0.59
Total |	185.97	295	0.63

Observations	**296**
F(16, 279)	2.15
Prob F	0.007
R-squared	0.1096
Adj R-square	**0.0586**
Root MSE	0.77037

ln_r1 |	Coef.	Std. Err	t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0036	0.0048	0.7600	0.4500	-0.0058	0.0130
day_employ~t |	0.0000	0.0000	-0.1000	0.9230	0.0000	0.0000
class_a |	-0.0409	0.1283	-0.3200	0.7500	-0.2936	0.2117
total_sf |	0.0000	0.0000	0.7800	0.4340	0.0000	0.0000
_1996_2000 |	0.1029	0.1693	0.6100	0.5440	-0.2305	0.4362
_1982_1995 |	-0.0977	0.1100	-0.8900	0.3750	-0.3143	0.1188
mkt_atlanta |	0.0390	0.2134	0.1800	0.8550	-0.3810	0.4590
mkt_boston |	-0.1461	0.1957	-0.7500	0.4560	-0.5314	0.2392
mkt_oakland |	0.1601	0.2587	0.6200	0.5360	-0.3491	0.6694
mkt_la |	0.3078	0.2079	1.4800	0.1400	-0.1015	0.7171
mkt_orange |	-0.3232	0.2067	-1.5600	0.1190	-0.7301	0.0836
mkt_sacram~o |	-0.4018	0.3227	-1.2500	0.2140	-1.0370	0.2334
mkt_san_de~o |	0.3133	0.3134	1.0000	0.3180	-0.3036	0.9301
mkt_san_fr~o |	0.3795	0.2225	1.7100	0.0890	-0.0586	0.8175
mkt_san_jose |	0.2693	0.2139	1.2600	0.2090	-0.1518	0.6904
mkt_seattle |	0.1541	0.2148	0.7200	0.4740	-0.2687	0.5769
_cons |	0.9827	0.2079	4.7300	0.0000	0.5734	1.3919

Dependant variable – Respondent 2

. regress ln_r2 noi_sf day_employment class_a total_sf _1996_2000 _1982_1995 mkt_atlantamkt _boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_franci sco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	3.41	16	0.21
Residual |	33.86	279	0.12
Total |	37.27	295	0.13

Observations	**296**
F(16, 279)	1.76
Prob F	0.0368
R-squared	0.0915
Adj R-square	**0.0394**
Root MSE	0.34839

ln_r2 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	-0.0008	0.0021	-0.3700	0.7120	-0.0050	0.0034
day_employ~t |	0.0000	0.0000	0.2900	0.7740	0.0000	0.0000
class_a |	-0.0428	0.0580	-0.7400	0.4620	-0.1570	0.0715
total_sf |	0.0000	0.0000	0.3000	0.7650	0.0000	0.0000
_1996_2000 |	-0.0515	0.0766	-0.6700	0.5020	-0.2023	0.0992
_1982_1995 |	-0.1039	0.0498	-2.0900	0.0380	-0.2018	-0.0059
mkt_atlanta |	0.0331	0.0965	0.3400	0.7320	-0.1568	0.2231
mkt_boston |	-0.0002	0.0885	0.0000	0.9980	-0.1745	0.1740
mkt_oakland |	0.0170	0.1170	0.1500	0.8850	-0.2133	0.2473
mkt_la |	-0.0825	0.0940	-0.8800	0.3810	-0.2676	0.1026
mkt_orange |	-0.0651	0.0935	-0.7000	0.4870	-0.2490	0.1189
mkt_sacram~o |	-0.0026	0.1459	-0.0200	0.9860	-0.2898	0.2847
mkt_san_de~o |	0.0513	0.1417	0.3600	0.7180	-0.2276	0.3303
mkt_san_fr~o |	-0.2544	0.1006	-2.5300	0.0120	-0.4525	-0.0563
mkt_san_jose |	0.0361	0.0967	0.3700	0.7090	-0.1544	0.2265
mkt_seattle |	-0.0935	0.0971	-0.9600	0.3370	-0.2847	0.0977
_cons |	1.7721	0.0940	18.8500	0.0000	1.5870	1.9572

Dependant variable – Respondent 4

. regress ln_r4 noi_sf day_employment class_a total_sf _1996_2000 _1982_1995 mkt_atlanta _boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_fr sco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	8.67	16	0.54
Residual |	49.26	279	0.18
Total |	57.93	295	0.20

Observations	**296**
F(16, 279)	3.07
Prob F	0.0001
R-squared	0.1497
Adj R-square	**0.101**
Root MSE	0.42017

ln_r4 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	-0.0034	0.0026	-1.3100	0.1930	-0.0085	0.0017
day_employ~t |	0.0000	0.0000	0.5900	0.5580	0.0000	0.0000
class_a |	-0.0057	0.0700	-0.0800	0.9350	-0.1435	0.1321
total_sf |	0.0000	0.0000	2.9900	0.0030	0.0000	0.0000
_1996_2000 |	0.0338	0.0924	0.3700	0.7150	-0.1481	0.2156
_1982_1995 |	-0.0776	0.0600	-1.2900	0.1970	-0.1958	0.0405
mkt_atlanta |	0.1507	0.1164	1.2900	0.1960	-0.0784	0.3798
mkt_boston |	0.1406	0.1068	1.3200	0.1890	-0.0695	0.3508
mkt_oakland |	0.4294	0.1411	3.0400	0.0030	0.1517	0.7072
mkt_la |	0.3903	0.1134	3.4400	0.0010	0.1670	0.6135
mkt_orange |	0.3147	0.1127	2.7900	0.0060	0.0928	0.5366
mkt_sacram~o |	-0.0885	0.1760	-0.5000	0.6150	-0.4350	0.2579
mkt_san_de~o |	-0.1990	0.1709	-1.1600	0.2450	-0.5354	0.1374
mkt_san_fr~o |	0.2546	0.1214	2.1000	0.0370	0.0157	0.4935
mkt_san_jose |	0.1845	0.1167	1.5800	0.1150	-0.0452	0.4142
mkt_seattle |	0.1769	0.1172	1.5100	0.1320	-0.0537	0.4075
_cons |	1.1847	0.1134	10.4500	0.0000	0.9614	1.4079

Dependant variable – Respondent 5

. regress ln_r5 noi_sf day_employment class_a total_sf _1996_2000 _1982_1995 mkt_atlanta _boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_fr sco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	24.69	16	1.54
Residual |	97.44	279	0.35
Total |	122.13	295	0.41

Observations	**296**
F(16, 279)	4.42
Prob F	0
R-squared	0.2022
Adj R-square	**0.1564**
Root MSE	0.59097

ln_r5 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	-0.0003	0.0036	-0.0700	0.9440	-0.0074	0.0069
day_employ~t |	0.0000	0.0000	1.1000	0.2720	0.0000	0.0000
class_a |	0.1005	0.0984	1.0200	0.3080	-0.0933	0.2943
total_sf |	0.0000	0.0000	-0.6800	0.4980	0.0000	0.0000
_1996_2000 |	-0.5534	0.1299	-4.2600	0.0000	-0.8091	-0.2977
_1982_1995 |	-0.1429	0.0844	-1.6900	0.0920	-0.3090	0.0232
mkt_atlanta |	0.5395	0.1637	3.3000	0.0010	0.2173	0.8617
mkt_boston |	0.5888	0.1502	3.9200	0.0000	0.2933	0.8844
mkt_oakland |	0.1806	0.1984	0.9100	0.3640	-0.2100	0.5713
mkt_la |	0.0346	0.1595	0.2200	0.8290	-0.2794	0.3486
mkt_orange |	0.3880	0.1585	2.4500	0.0150	0.0759	0.7001
mkt_sacram~o |	0.5299	0.2475	2.1400	0.0330	0.0426	1.0172
mkt_san_de~o |	0.0644	0.2404	0.2700	0.7890	-0.4088	0.5376
mkt_san_fr~o |	0.2329	0.1707	1.3600	0.1740	-0.1032	0.5689
mkt_san_jose |	0.2120	0.1641	1.2900	0.1970	-0.1110	0.5350
mkt_seattle |	0.5124	0.1648	3.1100	0.0020	0.1881	0.8368
_cons |	0.8664	0.1595	5.4300	0.0000	0.5524	1.1803

Dependant variable – Respondent 6

. regress ln_r6 noi_sf day_employment class_a total_sf _1996_2000 _1982_1995 mkt_atlanta _boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_fr sco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	4.06	16	0.25
Residual |	24.57	279	0.09
Total |	28.63	295	0.10

Observations	**296**
F(16, 279)	2.88
Prob F	0.0002
R-squared	0.1418
Adj R-square	**0.0926**
Root MSE	0.29678

ln_r6 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0025	0.0018	1.3700	0.1710	-0.0011	0.0061
day_employ~t |	0.0000	0.0000	-1.3100	0.1900	0.0000	0.0000
class_a |	0.0451	0.0494	0.9100	0.3620	-0.0522	0.1424
total_sf |	0.0000	0.0000	0.2400	0.8120	0.0000	0.0000
_1996_2000 |	-0.1333	0.0652	-2.0400	0.0420	-0.2617	-0.0049
_1982_1995 |	-0.1050	0.0424	-2.4800	0.0140	-0.1884	-0.0215
mkt_atlanta |	-0.0678	0.0822	-0.8200	0.4100	-0.2296	0.0940
mkt_boston |	0.1806	0.0754	2.3900	0.0170	0.0321	0.3290
mkt_oakland |	0.0419	0.0997	0.4200	0.6740	-0.1542	0.2381
mkt_la |	0.1140	0.0801	1.4200	0.1560	-0.0437	0.2717
mkt_orange |	0.0183	0.0796	0.2300	0.8180	-0.1384	0.1750
mkt_sacram~o |	0.1204	0.1243	0.9700	0.3340	-0.1243	0.3651
mkt_san_de~o |	0.0737	0.1207	0.6100	0.5420	-0.1639	0.3113
mkt_san_fr~o |	-0.1510	0.0857	-1.7600	0.0790	-0.3198	0.0177
mkt_san_jose |	-0.0977	0.0824	-1.1900	0.2370	-0.2599	0.0645
mkt_seattle |	0.0227	0.0827	0.2700	0.7840	-0.1402	0.1856
_cons |	1.5950	0.0801	19.9100	0.0000	1.4373	1.7527

Dependant variable – Respondent 7

. regress ln_r7 noi_sf day_employment class_a total_sf _1996_2000 _1982_1995 mkt_atlanta _boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_fr sco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	4.57	16	0.29
Residual |	23.02	279	0.08
Total |	27.59	295	0.09

Observations	**296**
F(16, 279)	3.46
Prob F	0
R-squared	0.1657
Adj R-square	**0.1179**
Root MSE	0.28724

ln_r7 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	-0.0022	0.0018	-1.2200	0.2240	-0.0056	0.0013
day_employ~t |	0.0000	0.0000	-1.8000	0.0730	0.0000	0.0000
class_a |	0.0849	0.0479	1.7700	0.0770	-0.0093	0.1791
total_sf |	0.0000	0.0000	1.9600	0.0510	0.0000	0.0000
_1996_2000 |	-0.1309	0.0631	-2.0700	0.0390	-0.2552	-0.0066
_1982_1995 |	-0.1117	0.0410	-2.7200	0.0070	-0.1924	-0.0309
mkt_atlanta |	-0.1717	0.0796	-2.1600	0.0320	-0.3284	-0.0151
mkt_boston |	-0.0792	0.0730	-1.0800	0.2790	-0.2228	0.0645
mkt_oakland |	-0.2589	0.0965	-2.6800	0.0080	-0.4488	-0.0691
mkt_la |	-0.1159	0.0775	-1.4900	0.1360	-0.2685	0.0367
mkt_orange |	-0.1640	0.0771	-2.1300	0.0340	-0.3157	-0.0123
mkt_sacram~o |	-0.3779	0.1203	-3.1400	0.0020	-0.6148	-0.1411
mkt_san_de~o |	-0.0448	0.1168	-0.3800	0.7020	-0.2748	0.1852
mkt_san_fr~o |	-0.1932	0.0830	-2.3300	0.0210	-0.3566	-0.0299
mkt_san_jose |	-0.2274	0.0798	-2.8500	0.0050	-0.3844	-0.0704
mkt_seattle |	-0.3347	0.0801	-4.1800	0.0000	-0.4923	-0.1770
_cons |	1.8936	0.0775	24.4300	0.0000	1.7411	2.0462

Dependant variable – Respondent 8

. regress ln_r8 noi_sf day_employment class_a total_sf _1996_2000 _1982_1995 mkt_atlanta _boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_fr sco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	33.59	16	3.00
Residual |	37.58	279	0.13
Total |	71.17	295	0.24

Observations	**296**
F(16, 279)	15.59
Prob F	0
R-squared	0.472
Adj R-square	**0.4417**
Root MSE	0.367

ln_r8 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0047	0.0023	2.0600	0.0400	0.0002	0.0091
day_employ~t |	0.0000	0.0000	1.5100	0.1320	0.0000	0.0000
class_a |	0.0741	0.0611	1.2100	0.2260	-0.0462	0.1945
total_sf |	0.0000	0.0000	6.8900	0.0000	0.0000	0.0000
_1996_2000 |	0.3931	0.0807	4.8700	0.0000	0.2343	0.5519
_1982_1995 |	0.2376	0.0524	4.5300	0.0000	0.1345	0.3408
mkt_atlanta |	-0.0856	0.1016	-0.8400	0.4000	-0.2857	0.1145
mkt_boston |	-0.1221	0.0932	-1.3100	0.1910	-0.3057	0.0615
mkt_oakland |	-0.1021	0.1232	-0.8300	0.4080	-0.3447	0.1405
mkt_la |	-0.0343	0.0991	-0.3500	0.7290	-0.2293	0.1607
mkt_orange |	-0.0081	0.0985	-0.0800	0.9340	-0.2019	0.1857
mkt_sacram~o |	-0.3906	0.1537	-2.5400	0.0120	-0.6932	-0.0880
mkt_san_de~o |	0.0486	0.1493	0.3300	0.7450	-0.2453	0.3425
mkt_san_fr~o |	-0.2828	0.1060	-2.6700	0.0080	-0.4914	-0.0741
mkt_san_jose |	-0.4277	0.1019	-4.2000	0.0000	-0.6283	-0.2271
mkt_seattle |	-0.3789	0.1023	-3.7000	0.0000	-0.5803	-0.1775
_cons |	1.0062	0.0990	10.1600	0.0000	0.8112	1.2012

Dependant variable – Respondent 9

. regress ln_r9 noi_sf day_employment class_a total_sf _1996_2000 _1982_1995 mkt_atlanta _boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_fr sco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	7.51	16	0.47
Residual |	31.67	279	0.11
Total |	39.18	295	0.13

Observations	**296**
F(16, 279)	4.14
Prob F	0
R-squared	0.1917
Adj R-square	**0.1453**
Root MSE	0.3369

ln_r9 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	-0.0006	0.0021	-0.2900	0.7760	-0.0047	0.0035
day_employ~t |	0.0000	0.0000	0.0300	0.9770	0.0000	0.0000
class_a |	0.0054	0.0561	0.1000	0.9240	-0.1051	0.1159
total_sf |	0.0000	0.0000	-3.3900	0.0010	0.0000	0.0000
_1996_2000 |	0.2225	0.0741	3.0000	0.0030	0.0767	0.3682
_1982_1995 |	0.1536	0.0481	3.1900	0.0020	0.0589	0.2484
mkt_atlanta |	0.2228	0.0933	2.3900	0.0180	0.0391	0.4065
mkt_boston |	-0.0323	0.0856	-0.3800	0.7060	-0.2008	0.1362
mkt_oakland |	0.1214	0.1131	1.0700	0.2840	-0.1013	0.3441
mkt_la |	-0.0283	0.0909	-0.3100	0.7560	-0.2073	0.1507
mkt_orange |	-0.0742	0.0904	-0.8200	0.4130	-0.2521	0.1038
mkt_sacram~o |	0.1027	0.1411	0.7300	0.4670	-0.1751	0.3805
mkt_san_de~o |	0.1736	0.1370	1.2700	0.2060	-0.0962	0.4434
mkt_san_fr~o |	0.0953	0.0973	0.9800	0.3280	-0.0963	0.2869
mkt_san_jose |	0.1051	0.0936	1.1200	0.2620	-0.0790	0.2893
mkt_seattle |	-0.0305	0.0939	-0.3200	0.7460	-0.2154	0.1544
_cons |	1.5737	0.0909	17.3100	0.0000	1.3947	1.7527

Dependant variable – Respondent 11

. regress ln_r11 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	SS	df	MS		
				Observations	**296**
				F(16, 279)	4
Model |	8.36	16	0.52	Prob F	0
Residual |	36.41	279	0.13	R-squared	0.1868
				Adj R-square	**0.1401**
Total |	44.77	295	0.15	Root MSE	0.36125

ln_r11 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0018	0.0022	0.8200	0.4110	-0.0026	0.0062
day_employ~t |	0.0000	0.0000	0.6200	0.5390	0.0000	0.0000
class_a |	-0.0367	0.0602	-0.6100	0.5430	-0.1551	0.0818
total_sf |	0.0000	0.0000	0.9300	0.3560	0.0000	0.0000
_1996_2000 |	0.1676	0.0794	2.1100	0.0360	0.0113	0.3239
_1982_1995 |	-0.1516	0.0516	-2.9400	0.0040	-0.2532	-0.0500
mkt_atlanta |	-0.0230	0.1001	-0.2300	0.8190	-0.2199	0.1740
mkt_boston |	0.0443	0.0918	0.4800	0.6300	-0.1364	0.2250
mkt_oakland |	-0.1208	0.1213	-1.0000	0.3200	-0.3596	0.1180
mkt_la |	-0.1727	0.0975	-1.7700	0.0780	-0.3646	0.0193
mkt_orange |	-0.2601	0.0969	-2.6800	0.0080	-0.4509	-0.0693
mkt_sacram~o |	-0.0876	0.1513	-0.5800	0.5630	-0.3855	0.2102
mkt_san_de~o |	-0.1561	0.1469	-1.0600	0.2890	-0.4454	0.1332
mkt_san_fr~o |	-0.0962	0.1044	-0.9200	0.3580	-0.3016	0.1092
mkt_san_jose |	-0.1573	0.1003	-1.5700	0.1180	-0.3548	0.0402
mkt_seattle |	-0.2239	0.1007	-2.2200	0.0270	-0.4222	-0.0256
_cons |	1.5459	0.0975	15.8600	0.0000	1.3540	1.7378

Dependant variable – Respondent 12

. regress ln_r12 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	SS	df	MS		
				Observations	**296**
				F(16, 279)	3.92
Model |	19.87	16	1.24	Prob F	0
Residual |	88.43	279	0.32	R-squared	0.1835
				Adj R-square	**0.1367**
Total |	108.30	295	0.37	Root MSE	0.56297

ln_r12 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	-0.0008	0.0035	-0.2200	0.8280	-0.0076	0.0061
day_employ~t |	0.0000	0.0000	1.6000	0.1100	0.0000	0.0000
class_a |	-0.1324	0.0938	-1.4100	0.1590	-0.3171	0.0522
total_sf |	0.0000	0.0000	1.1700	0.2420	0.0000	0.0000
_1996_2000 |	0.1270	0.1238	1.0300	0.3060	-0.1166	0.3706
_1982_1995 |	-0.0762	0.0804	-0.9500	0.3440	-0.2344	0.0821
mkt_atlanta |	0.2164	0.1559	1.3900	0.1660	-0.0906	0.5233
mkt_boston |	-0.1362	0.1430	-0.9500	0.3420	-0.4177	0.1454
mkt_oakland |	-0.4599	0.1890	-2.4300	0.0160	-0.8320	-0.0877
mkt_la |	0.2623	0.1520	1.7300	0.0850	-0.0368	0.5614
mkt_orange |	-0.3701	0.1510	-2.4500	0.0150	-0.6674	-0.0728
mkt_sacram~o |	-0.1311	0.2358	-0.5600	0.5790	-0.5953	0.3331
mkt_san_de~o |	0.0109	0.2290	0.0500	0.9620	-0.4399	0.4616
mkt_san_fr~o |	-0.1367	0.1626	-0.8400	0.4010	-0.4568	0.1834
mkt_san_jose |	-0.2927	0.1563	-1.8700	0.0620	-0.6005	0.0150
mkt_seattle |	-0.3141	0.1570	-2.0000	0.0460	-0.6231	-0.0051
_cons |	1.2491	0.1519	8.2200	0.0000	0.9500	1.5481

Dependant variable – Respondent 13

. regress ln_r13 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	28.53	16	1.78
Residual |	71.89	279	0.26
Total |	100.41	295	0.34

Observations	**296**
F(16, 279)	6.92
Prob F	0
R-squared	0.2841
Adj R-square	**0.243**
Root MSE	0.5076

ln_r13 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0045	0.0031	1.4400	0.1500	-0.0016	0.0107
day_employ~t |	0.0000	0.0000	3.0800	0.0020	0.0000	0.0000
class_a |	0.1297	0.0846	1.5300	0.1260	-0.0368	0.2962
total_sf |	0.0000	0.0000	1.4200	0.1580	0.0000	0.0000
_1996_2000 |	-0.7157	0.1116	-6.4100	0.0000	-0.9354	-0.4961
_1982_1995 |	-0.3758	0.0725	-5.1800	0.0000	-0.5185	-0.2331
mkt_atlanta |	0.2789	0.1406	1.9800	0.0480	0.0022	0.5557
mkt_boston |	-0.1812	0.1290	-1.4100	0.1610	-0.4351	0.0727
mkt_oakland |	0.1503	0.1705	0.8800	0.3790	-0.1852	0.4858
mkt_la |	-0.1410	0.1370	-1.0300	0.3040	-0.4107	0.1287
mkt_orange |	0.1465	0.1362	1.0800	0.2830	-0.1216	0.4145
mkt_sacram~o |	0.0809	0.2126	0.3800	0.7040	-0.3376	0.4995
mkt_san_de~o |	0.0101	0.2065	0.0500	0.9610	-0.3963	0.4166
mkt_san_fr~o |	-0.0736	0.1466	-0.5000	0.6160	-0.3622	0.2151
mkt_san_jose |	0.0278	0.1409	0.2000	0.8440	-0.2497	0.3053
mkt_seattle |	0.1759	0.1415	1.2400	0.2150	-0.1027	0.4545
_cons |	1.1690	0.1370	8.5300	0.0000	0.8993	1.4386

Dependant variable – Respondent 15

. regress ln_r15 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	10.19	16	0.64
Residual |	37.75	279	0.14
Total |	47.94	295	0.16

Observations	**296**
F(16, 279)	4.71
Prob F	0
R-squared	0.2126
Adj R-square	**0.1675**
Root MSE	0.36781

ln_r15 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0017	0.0023	0.7500	0.4540	-0.0028	0.0062
day_employ~t |	0.0000	0.0000	0.9500	0.3430	0.0000	0.0000
class_a |	0.0172	0.0613	0.2800	0.7790	-0.1034	0.1378
total_sf |	0.0000	0.0000	0.2500	0.8050	0.0000	0.0000
_1996_2000 |	0.4520	0.0809	5.5900	0.0000	0.2929	0.6112
_1982_1995 |	0.0978	0.0525	1.8600	0.0640	-0.0056	0.2012
mkt_atlanta |	-0.1244	0.1019	-1.2200	0.2230	-0.3250	0.0761
mkt_boston |	0.1201	0.0935	1.2900	0.2000	-0.0639	0.3041
mkt_oakland |	-0.0001	0.1235	0.0000	0.9990	-0.2433	0.2430
mkt_la |	-0.0642	0.0993	-0.6500	0.5180	-0.2596	0.1312
mkt_orange |	-0.2261	0.0987	-2.2900	0.0230	-0.4204	-0.0319
mkt_sacram~o |	0.0166	0.1541	0.1100	0.9140	-0.2867	0.3199
mkt_san_de~o |	-0.0245	0.1496	-0.1600	0.8700	-0.3190	0.2701
mkt_san_fr~o |	-0.1789	0.1063	-1.6800	0.0930	-0.3880	0.0303
mkt_san_jose |	-0.0875	0.1021	-0.8600	0.3920	-0.2886	0.1135
mkt_seattle |	-0.0982	0.1026	-0.9600	0.3390	-0.3001	0.1037
_cons |	1.3565	0.0993	13.6700	0.0000	1.1611	1.5519

Dependant variable – Respondent 16

. regress ln_r16 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	27.43	16	1.71
Residual |	90.74	279	0.33
Total |	118.16	295	0.45

Observations	**296**
F(16, 279)	5.27
Prob F	0
R-squared	0.2321
Adj R-square	**0.1881**
Root MSE	0.57028

ln_r16 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0013	0.0035	0.3700	0.7130	-0.0056	0.0082
day_employ~t |	0.0000	0.0000	0.4500	0.6520	0.0000	0.0000
class_a |	-0.0337	0.0950	-0.3500	0.7230	-0.2207	0.1534
total_sf |	0.0000	0.0000	1.3200	0.1880	0.0000	0.0000
_1996_2000 |	0.6904	0.1254	5.5100	0.0000	0.4436	0.9371
_1982_1995 |	0.3958	0.0814	4.8600	0.0000	0.2354	0.5561
mkt_atlanta |	-0.2422	0.1580	-1.5300	0.1260	-0.5531	0.0687
mkt_boston |	-0.3324	0.1449	-2.2900	0.0230	-0.6176	-0.0471
mkt_oakland |	-0.1444	0.1915	-0.7500	0.4520	-0.5213	0.2326
mkt_la |	-0.1868	0.1539	-1.2100	0.2260	-0.4898	0.1162
mkt_orange |	-0.4979	0.1530	-3.2500	0.0010	-0.7990	-0.1967
mkt_sacram~o |	-0.6367	0.2389	-2.6700	0.0080	-1.1069	-0.1665
mkt_san_de~o |	-0.2971	0.2320	-1.2800	0.2010	-0.7538	0.1595
mkt_san_fr~o |	-0.5599	0.1647	-3.4000	0.0010	-0.8842	-0.2356
mkt_san_jose |	-0.1120	0.1584	-0.7100	0.4800	-0.4238	0.1997
mkt_seattle |	-0.4485	0.1590	-2.8200	0.0050	-0.7615	-0.1355
_cons |	1.1927	0.1539	7.7500	0.0000	0.8897	1.4956

Dependant variable – Respondent 17

. regress ln_r17 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	SS	df	MS		
				Observations	**296**
				F(16, 279)	7.35
Model |	30.13	16	1.88	Prob F	0
Residual |	71.48	279	0.26	R-squared	0.2965
				Adj R-square	**0.2562**
Total |	101.61	295	0.34	Root MSE	0.50617

ln_r17 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0007	0.0031	0.2200	0.8250	-0.0055	0.0068
day_employ~t |	0.0000	0.0000	1.9100	0.0570	0.0000	0.0000
class_a |	0.0556	0.0843	0.6600	0.5100	-0.1104	0.2216
total_sf |	0.0000	0.0000	0.9600	0.3390	0.0000	0.0000
_1996_2000 |	-0.5034	0.1113	-4.5200	0.0000	-0.7224	-0.2843
_1982_1995 |	-0.3936	0.0723	-5.4400	0.0000	-0.5359	-0.2513
mkt_atlanta |	0.5781	0.1402	4.1200	0.0000	0.3021	0.8541
mkt_boston |	0.2737	0.1286	2.1300	0.0340	0.0205	0.5269
mkt_oakland |	-0.0390	0.1700	-0.2300	0.8190	-0.3736	0.2956
mkt_la |	0.0680	0.1366	0.5000	0.6190	-0.2010	0.3369
mkt_orange |	-0.0275	0.1358	-0.2000	0.8400	-0.2948	0.2399
mkt_sacram~o |	0.2458	0.2120	1.1600	0.2470	-0.1715	0.6632
mkt_san_de~o |	0.3819	0.2059	1.8500	0.0650	-0.0234	0.7872
mkt_san_fr~o |	0.0399	0.1462	0.2700	0.7850	-0.2480	0.3277
mkt_san_jose |	0.1688	0.1406	1.2000	0.2310	-0.1078	0.4455
mkt_seattle |	-0.0173	0.1411	-0.1200	0.9030	-0.2951	0.2605
_cons |	0.9665	0.1366	7.0800	0.0000	0.6976	1.2354

Dependant variable – Respondent 18

. regress ln_r18 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	**SS**	**df**	**MS**
Model |	7.26	16	0.45
Residual |	25.00	279	0.09
Total |	32.26	295	0.19

Observations	**296**
F(16, 279)	5.06
Prob F	0
R-squared	0.2251
Adj R-square	**0.1806**
Root MSE	0.29932

ln_r18 |	**Coef.**	**Std. Err**	**. t**	**P|t|**	**[95% Conf.**	**Interval]**
noi_sf |	0.0016	0.0018	0.8500	0.3970	-0.0021	0.0052
day_employ~t |	0.0000	0.0000	3.0600	0.0020	0.0000	0.0000
class_a |	-0.0371	0.0499	-0.7400	0.4580	-0.1352	0.0611
total_sf |	0.0000	0.0000	2.3400	0.0200	0.0000	0.0000
_1996_2000 |	0.1874	0.0658	2.8500	0.0050	0.0579	0.3169
_1982_1995 |	0.0603	0.0427	1.4100	0.1590	-0.0238	0.1445
mkt_atlanta |	0.1461	0.0829	1.7600	0.0790	-0.0171	0.3093
mkt_boston |	0.0813	0.0760	1.0700	0.2860	-0.0684	0.2310
mkt_oakland |	-0.0109	0.1005	-0.1100	0.9140	-0.2088	0.1869
mkt_la |	0.0015	0.0808	0.0200	0.9850	-0.1575	0.1606
mkt_orange |	-0.0431	0.0803	-0.5400	0.5920	-0.2012	0.1150
mkt_sacram~o |	0.0515	0.1254	0.4100	0.6820	-0.1953	0.2983
mkt_san_de~o |	-0.0667	0.1218	-0.5500	0.5840	-0.3064	0.1730
mkt_san_fr~o |	-0.0053	0.0865	-0.0600	0.9510	-0.1755	0.1649
mkt_san_jose |	-0.1422	0.0831	-1.7100	0.0880	-0.3058	0.0214
mkt_seattle |	-0.1196	0.0835	-1.4300	0.1530	-0.2839	0.0447
_cons |	1.5062	0.0808	18.6500	0.0000	1.3472	1.6652

Dependant variable – Respondent 19

. regress ln_r19 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	**SS**	**df**	**MS**			
					Observations	**296**
					F(16, 279)	5.02
Model |	10.78	16	0.67		Prob F	0
Residual |	37.40	279	0.13		R-squared	0.2237
					Adj R-square	**0.1792**
Total |	48.18	295	0.16		Root MSE	0.36612

ln_r19 |	**Coef.**	**Std. Err**	**. t**	**P|t|**	**[95% Conf.**	**Interval]**
noi_sf |	0.0010	0.0023	0.4400	0.6600	-0.0035	0.0054
day_employ~t |	0.0000	0.0000	2.4200	0.0160	0.0000	0.0000
class_a |	-0.0477	0.0610	-0.7800	0.4350	-0.1677	0.0724
total_sf |	0.0000	0.0000	2.5700	0.0110	0.0000	0.0000
_1996_2000 |	-0.1651	0.0805	-2.0500	0.0410	-0.3235	-0.0066
_1982_1995 |	-0.0183	0.0523	-0.3500	0.7270	-0.1212	0.0847
mkt_atlanta |	0.5224	0.1014	5.1500	0.0000	0.3228	0.7220
mkt_boston |	0.1814	0.0930	1.9500	0.0520	-0.0017	0.3645
mkt_oakland |	0.2579	0.1229	2.1000	0.0370	0.0159	0.4999
mkt_la |	0.0838	0.0988	0.8500	0.3970	-0.1108	0.2783
mkt_orange |	0.1688	0.0982	1.7200	0.0870	-0.0246	0.3621
mkt_sacram~o |	0.1430	0.1534	0.9300	0.3520	-0.1589	0.4449
mkt_san_de~o |	0.1943	0.1489	1.3000	0.1930	-0.0989	0.4874
mkt_san_fr~o |	0.0769	0.1058	0.7300	0.4680	-0.1313	0.2851
mkt_san_jose |	0.1089	0.1017	1.0700	0.2850	-0.0912	0.3090
mkt_seattle |	0.1262	0.1021	1.2400	0.2170	-0.0747	0.3272
_cons |	1.1554	0.0988	11.6900	0.0000	0.9609	1.3499

Dependant variable – Respondent 20

. regress ln_r20 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	SS	df	MS		
				Observations	**296**
				F(16, 279)	6.69
Model |	9.15	16	0.57	Prob F	0
Residual |	23.84	279	0.09	R-squared	0.2774
				Adj R-square	**0.2359**
Total |	32.99	295	0.11	Root MSE	0.29229

ln_r20 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0020	0.0018	1.1300	0.2600	-0.0015	0.0056
day_employ~t |	0.0000	0.0000	1.0500	0.2960	0.0000	0.0000
class_a |	0.0936	0.0487	1.9200	0.0560	-0.0022	0.1895
total_sf |	0.0000	0.0000	4.6200	0.0000	0.0000	0.0000
_1996_2000 |	-0.0916	0.0643	-1.4300	0.1550	-0.2181	0.0349
_1982_1995 |	-0.0536	0.0417	-1.2800	0.2000	-0.1358	0.0286
mkt_atlanta |	0.0219	0.0810	0.2700	0.7870	-0.1374	0.1813
mkt_boston |	0.0882	0.0743	1.1900	0.2360	-0.0580	0.2344
mkt_oakland |	-0.0391	0.0982	-0.4000	0.6910	-0.2323	0.1541
mkt_la |	0.1505	0.0789	1.9100	0.0570	-0.0048	0.3058
mkt_orange |	-0.0588	0.0784	-0.7500	0.4540	-0.2131	0.0956
mkt_sacram~o |	-0.0997	0.1224	-0.8100	0.4160	-0.3407	0.1413
mkt_san_de~o |	-0.0982	0.1189	-0.8300	0.4100	-0.3322	0.1359
mkt_san_fr~o |	-0.1045	0.0844	-1.2400	0.2170	-0.2707	0.0617
mkt_san_jose |	-0.0595	0.0812	-0.7300	0.4640	-0.2192	0.1003
mkt_seattle |	-0.1596	0.0815	-1.9600	0.0510	0.31996_20007	0.0008
_cons |	1.4445	0.0789	18.3100	0.0000	1.2892	1.5997

Dependant variable – Respondent 21

. regress ln_r21 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	8.66	16	0.54
Residual |	22.69	279	0.08
Total |	31.35	295	0.16

Observations	**296**
F(16, 279)	6.65
Prob F	0
R-squared	0.2761
Adj R-square	**0.2346**
Root MSE	0.2852

ln_r21 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0009	0.0018	0.4900	0.6210	-0.0026	0.0043
day_employ~t |	0.0000	0.0000	2.8000	0.0060	0.0000	0.0000
class_a |	-0.1279	0.0475	-2.6900	0.0080	-0.2214	-0.0343
total_sf |	0.0000	0.0000	3.1500	0.0020	0.0000	0.0000
_1996_2000 |	-0.0242	0.0627	-0.3900	0.7000	-0.1476	0.0993
_1982_1995 |	-0.0976	0.0407	-2.4000	0.0170	-0.1778	-0.0175
mkt_atlanta |	0.2058	0.0790	2.6100	0.0100	0.0503	0.3613
mkt_boston |	-0.1633	0.0725	-2.2500	0.0250	-0.3060	-0.0207
mkt_oakland |	-0.1214	0.0958	-1.2700	0.2060	-0.3099	0.0671
mkt_la |	-0.0023	0.0770	-0.0300	0.9760	-0.1539	0.1492
mkt_orange |	-0.0612	0.0765	-0.8000	0.4250	-0.2118	0.0894
mkt_sacram~o |	0.0620	0.1195	0.5200	0.6040	-0.1732	0.2971
mkt_san_de~o |	0.1587	0.1160	1.3700	0.1720	-0.0697	0.3871
mkt_san_fr~o |	-0.2009	0.0824	-2.4400	0.0150	-0.3631	-0.0388
mkt_san_jose |	-0.0483	0.0792	-0.6100	0.5430	-0.2042	0.1076
mkt_seattle |	-0.0535	0.0795	-0.6700	0.5010	-0.2101	0.1030
_cons |	1.7957	0.0770	23.3300	0.0000	1.6442	1.9472

Dependant variable – Respondent 22

. regress ln_r22 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	**SS**	**df**	**MS**
Model |	4.72	16	0.30
Residual |	16.93	279	0.06
Total |	21.65	295	0.07

Observations	**296**
F(16, 279)	4.86
Prob F	0
R-squared	0.218
Adj R-square	**0.1732**
Root MSE	0.24634

ln_r22 |	**Coef.**	**Std. Err**	**. t**	**P|t|**	**[95% Conf.**	**Interval]**
noi_sf |	0.0008	0.0015	0.5000	0.6180	-0.0022	0.0037
day_employ~t |	0.0000	0.0000	2.3100	0.0220	0.0000	0.0000
class_a |	-0.0072	0.0410	-0.1700	0.8620	-0.0879	0.0736
total_sf |	0.0000	0.0000	-2.1300	0.0340	0.0000	0.0000
_1996_2000 |	0.0414	0.0542	0.7700	0.4450	-0.0652	0.1480
_1982_1995 |	0.0023	0.0352	0.0700	0.9470	-0.0669	0.0716
mkt_atlanta |	-0.1688	0.0682	-2.4700	0.0140	-0.3031	-0.0345
mkt_boston |	0.2020	0.0626	3.2300	0.0010	0.0788	0.3252
mkt_oakland |	-0.0409	0.0827	-0.4900	0.6220	-0.2037	0.1220
mkt_la |	0.0996	0.0665	1.5000	0.1350	-0.0313	0.2305
mkt_orange |	0.0039	0.0661	0.0600	0.9530	-0.1262	0.1340
mkt_sacram~o |	0.0008	0.1032	0.0100	0.9940	-0.2023	0.2039
mkt_san_de~o |	-0.0771	0.1002	-0.7700	0.4430	-0.2743	0.1202
mkt_san_fr~o |	0.0722	0.0712	1.0100	0.3110	-0.0679	0.2123
mkt_san_jose |	-0.0770	0.0684	-1.1300	0.2610	-0.2117	0.0576
mkt_seattle |	0.0030	0.0687	0.0400	0.9650	-0.1322	0.1382
_cons |	1.5943	0.0665	23.9800	0.0000	1.4635	1.7252

Dependant variable – Respondent 23

. regress ln_r23 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	1.97	16	0.12
Residual |	16.19	279	0.06
Total |	18.16	295	0.06

Observations	**296**
F(16, 279)	2.12
Prob F	0.0079
R-squared	0.1083
Adj R-square	**0.0572**
Root MSE	0.24089

ln_r23 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	-0.0016	0.0015	-1.0600	0.2920	-0.0045	0.0014
day_employ~t |	0.0000	0.0000	-0.3800	0.7060	0.0000	0.0000
class_a |	-0.0307	0.0401	-0.7700	0.4450	-0.1097	0.0483
total_sf |	0.0000	0.0000	2.3200	0.0210	0.0000	0.0000
_1996_2000 |	0.0378	0.0530	0.7100	0.4760	-0.0665	0.1420
_1982_1995 |	-0.0313	0.0344	-0.9100	0.3640	-0.0990	0.0364
mkt_atlanta |	0.0885	0.0667	1.3300	0.1860	-0.0428	0.2198
mkt_boston |	0.1009	0.0612	1.6500	0.1000	-0.0196	0.2214
mkt_oakland |	-0.0191	0.0809	-0.2400	0.8130	-0.1784	0.1401
mkt_la |	0.0088	0.0650	0.1400	0.8920	-0.1192	0.1368
mkt_orange |	-0.0507	0.0646	-0.7800	0.4340	-0.1779	0.0766
mkt_sacram~o |	0.1083	0.1009	1.0700	0.2840	-0.0903	0.3069
mkt_san_de~o |	-0.1282	0.0980	-1.3100	0.1920	-0.3211	0.0647
mkt_san_fr~o |	0.0536	0.0696	0.7700	0.4410	-0.0833	0.1906
mkt_san_jose |	0.0012	0.0669	0.0200	0.9860	-0.1305	0.1329
mkt_seattle |	-0.1026	0.0672	-1.5300	0.1280	-0.2348	0.0297
_cons |	1.6830	0.0650	25.8900	0.0000	1.5550	1.8109

Dependant variable – Respondent 24

. regress ln_r24 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	26.36	16	1.65
Residual |	49.62	279	0.18
Total |	75.98	295	0.26

Observations	**296**
F(16, 279)	9.26
Prob F	0
R-squared	0.347
Adj R-square	**0.3095**
Root MSE	0.42172

ln_r24 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0015	0.0026	0.5600	0.5770	-0.0037	0.0066
day_employ~t |	0.0000	0.0000	2.0200	0.0440	0.0000	0.0000
class_a |	0.2039	0.0703	2.9000	0.0040	0.0656	0.3422
total_sf |	0.0000	0.0000	5.6300	0.0000	0.0000	0.0000
_1996_2000 |	-0.0377	0.0927	-0.4100	0.6840	-0.2202	0.1448
_1982_1995 |	-0.0177	0.0602	-0.2900	0.7690	-0.1363	0.1008
mkt_atlanta |	-0.3006	0.1168	-2.5700	0.0110	-0.5306	-0.0707
mkt_boston |	-0.0574	0.1071	-0.5400	0.5930	-0.2683	0.1536
mkt_oakland |	-0.2882	0.1416	-2.0300	0.0430	-0.5669	-0.0094
mkt_la |	-0.2380	0.1138	-2.0900	0.0370	-0.4620	-0.0139
mkt_orange |	-0.2774	0.1131	-2.4500	0.0150	-0.5001	-0.0547
mkt_sacram~o |	-0.4008	0.1766	-2.2700	0.0240	-0.7485	-0.0531
mkt_san_de~o |	0.0559	0.1715	0.3300	0.7450	-0.2817	0.3936
mkt_san_fr~o |	-0.1390	0.1218	-1.1400	0.2550	-0.3788	0.1008
mkt_san_jose |	-0.1074	0.1171	-0.9200	0.3600	-0.3379	0.1232
mkt_seattle |	-0.3566	0.1176	-3.0300	0.0030	-0.5881	-0.1252
_cons |	1.3722	0.1138	12.0600	0.0000	1.1481	1.5962

Dependant variable – Respondent 25

. regress ln_r25 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	**SS**	**df**	**MS**
Model |	3.54	16	0.22
Residual |	11.98	279	0.04
Total |	15.51	295	0.05

Observations	**296**
F(16, 279)	5.15
Prob F	0
R-squared	0.228
Adj R-square	**0.1837**
Root MSE	0.20719

ln_r25 |	**Coef.**	**Std. Err**	**. t**	**P|t|**	**[95% Conf.**	**Interval]**
noi_sf |	-0.0008	0.0013	-0.6200	0.5350	-0.0033	0.0017
day_employ~t |	0.0000	0.0000	1.1400	0.2550	0.0000	0.0000
class_a |	-0.0075	0.0345	-0.2200	0.8290	-0.0754	0.0605
total_sf |	0.0000	0.0000	-0.8100	0.4180	0.0000	0.0000
_1996_2000 |	0.1012	0.0455	2.2200	0.0270	0.0116	0.1909
_1982_1995 |	-0.0448	0.0296	-1.5100	0.1310	-0.1031	0.0134
mkt_atlanta |	0.1058	0.0574	1.8400	0.0660	-0.0072	0.2188
mkt_boston |	0.1298	0.0526	2.4600	0.0140	0.0261	0.2334
mkt_oakland |	0.0188	0.0696	0.2700	0.7870	-0.1181	0.1558
mkt_la |	-0.0388	0.0559	-0.6900	0.4890	-0.1488	0.0713
mkt_orange |	-0.1325	0.0556	-2.3800	0.0180	-0.2419	-0.0231
mkt_sacram~o |	-0.0438	0.0868	-0.5000	0.6140	-0.2147	0.1270
mkt_san_de~o |	-0.0321	0.0843	-0.3800	0.7040	-0.1980	0.1338
mkt_san_fr~o |	0.0398	0.0599	0.6600	0.5070	-0.0780	0.1576
mkt_san_jose |	-0.1180	0.0575	-2.0500	0.0410	-0.2312	-0.0047
mkt_seattle |	-0.0557	0.0578	-0.9600	0.3360	-0.1694	0.0580
_cons |	1.5182	0.0559	27.1500	0.0000	1.4081	1.6282

Dependant variable – Respondent 26

. regress ln_r26 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	16.49	16	10.03
Residual |	86.52	279	0.31
Total |	103.00	295	0.35

Observations	**296**
F(16, 279)	3.32
Prob F	0
R-squared	0.1601
Adj R-square	**0.1119**
Root MSE	0.55686

ln_r26 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0014	0.0034	0.4100	0.6800	-0.0053	0.0082
day_employ~t |	0.0000	0.0000	-3.4900	0.0010	0.0000	0.0000
class_a |	-0.0533	0.0928	-0.5700	0.5660	-0.2359	0.1293
total_sf |	0.0000	0.0000	0.4200	0.6780	0.0000	0.0000
_1996_2000 |	-0.1798	0.1224	-1.4700	0.1430	-0.4207	0.0612
_1982_1995 |	-0.1287	0.0795	-1.6200	0.1070	-0.2852	0.0279
mkt_atlanta |	-0.6637	0.1542	-4.3000	0.0000	-0.9673	-0.3601
mkt_boston |	0.0726	0.1415	0.5100	0.6080	-0.2059	0.3512
mkt_oakland |	0.1003	0.1870	0.5400	0.5920	-0.2678	0.4684
mkt_la |	-0.1550	0.1503	-1.0300	0.3030	-0.4509	0.1409
mkt_orange |	0.0397	0.1494	0.2700	0.7900	-0.2543	0.3338
mkt_sacram~o |	0.1809	0.2333	0.7800	0.4390	-0.2783	0.6401
mkt_san_de~o |	0.0692	0.2265	0.3100	0.7600	-0.3767	0.5151
mkt_san_fr~o |	-0.1357	0.1609	-0.8400	0.4000	-0.4523	0.1810
mkt_san_jose |	-0.1898	0.1546	-1.2300	0.2210	-0.4942	0.1146
mkt_seattle |	-0.1346	0.1553	-0.8700	0.3870	-0.4402	0.1710
_cons |	1.6459	0.1503	10.9500	0.0000	1.3500	1.9417

Dependant variable – Respondent 27

. regress ln_r27 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	SS	df	MS		
				Observations	**296**
				F(16, 279)	2.68
Model |	8.55	16	0.53	Prob F	0.0006
Residual |	55.59	279	0.20	R-squared	0.1333
				Adj R-square	**0.0836**
Total |	64.14	295	0.22	Root MSE	0.44635

ln_r27 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0016	0.0028	0.5700	0.5700	-0.0039	0.0070
day_employ~t |	0.0000	0.0000	0.5000	0.6190	0.0000	0.0000
class_a |	-0.0641	0.0744	-0.8600	0.3900	-0.2105	0.0823
total_sf |	0.0000	0.0000	1.7800	0.0770	0.0000	0.0000
_1996_2000 |	0.2814	0.0981	2.8700	0.0040	0.0882	0.4745
_1982_1995 |	0.1533	0.0637	2.4000	0.0170	0.0278	0.2788
mkt_atlanta |	0.1073	0.1236	0.8700	0.3860	-0.1361	0.3506
mkt_boston |	-0.0084	0.1134	-0.0700	0.9410	-0.2316	0.2149
mkt_oakland |	0.3917	0.1499	2.6100	0.0090	0.0967	0.6868
mkt_la |	-0.1354	0.1205	-1.1200	0.2620	-0.3726	0.1017
mkt_orange |	0.0227	0.1197	0.1900	0.8500	-0.2130	0.2584
mkt_sacram~o |	-0.3519	0.1870	-1.8800	0.0610	-0.7199	0.0161
mkt_san_de~o |	0.0031	0.1816	0.0200	0.9860	-0.3543	0.3605
mkt_san_fr~o |	0.1077	0.1289	0.8400	0.4040	-0.1461	0.3616
mkt_san_jose |	-0.0530	0.1239	-0.4300	0.6690	-0.2969	0.1910
mkt_seattle |	-0.0663	0.1245	-0.5300	0.5950	-0.3113	0.1787
_cons |	1.4190	0.1205	11.7800	0.0000	1.1819	1.6561

Dependant variable – Respondent 28

. regress ln_r28 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	18.98	16	1.19
Residual |	64.65	279	0.23
Total |	83.64	295	0.28

Observations	**296**
F(16, 279)	5.12
Prob F	0
R-squared	0.227
Adj R-square	**0.1826**
Root MSE	0.48139

ln_r28 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	-0.0002	0.0030	-0.0700	0.9470	-0.0060	0.0056
day_employ~t |	0.0000	0.0000	0.4600	0.6470	0.0000	0.0000
class_a |	-0.0305	0.0802	-0.3800	0.7040	-0.1883	0.1274
total_sf |	0.0000	0.0000	0.0900	0.9310	0.0000	0.0000
_1996_2000 |	-0.1889	0.1058	-1.7900	0.0750	-0.3972	0.0194
_1982_1995 |	-0.3723	0.0688	-5.4200	0.0000	-0.5076	-0.2370
mkt_atlanta |	0.1493	0.1333	1.1200	0.2640	-0.1131	0.4118
mkt_boston |	-0.1136	0.1223	-0.9300	0.3540	-0.3544	0.1271
mkt_oakland |	0.0627	0.1617	0.3900	0.6990	-0.2555	0.3809
mkt_la |	-0.1434	0.1299	-1.1000	0.2710	-0.3992	0.1123
mkt_orange |	-0.2284	0.1291	-1.7700	0.0780	-0.4826	0.0259
mkt_sacram~o |	-0.5017	0.2016	-2.4900	0.0130	-0.8986	-0.1048
mkt_san_de~o |	-0.0654	0.1958	-0.3300	0.7390	-0.4509	).31996_200087
mkt_san_fr~o |	0.0906	0.1391	0.6500	0.5150	-0.1831	0.3643
mkt_san_jose |	-0.3542	0.1337	-2.6500	0.0090	-0.6174	-0.0911
mkt_seattle |	0.1278	0.1342	0.9500	0.3420	-0.1364	0.3920
_cons |	1.7402	0.1299	13.4000	0.0000	1.4845	1.9959

Dependant variable – Respondent 29

. regress ln_r29 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	**SS**	**df**	**MS**		
				F(16, 279)	1.22
Model |	1.71	16	0.17	Prob F	0.253
Residual |	24.41	279	0.09	R-squared	0.0653
				Adj R-square	**0.0117**
Total |	26.11	295	0.088511982_1995	Root MSE	0.29576

Observations **296**

ln_r29 |	**Coef.**	**Std. Err**	**. t**	**P|t|**	**[95% Conf.**	**Interval]**
noi_sf |	0.0004	0.0018	0.2400	0.8100	-0.0032	0.0040
day_employ~t |	0.0000	0.0000	0.9100	0.3610	0.0000	0.0000
class_a |	-0.0423	0.0493	-0.8600	0.3920	-0.1393	0.0547
total_sf |	0.0000	0.0000	1.3900	0.1660	0.0000	0.0000
_1996_2000 |	0.0269	0.0650	0.4100	0.6790	-0.1010	0.1549
_1982_1995 |	-0.0428	0.0422	-1.0100	0.3120	-0.1260	0.0403
mkt_atlanta |	0.1312	0.0819	1.6000	0.1100	-0.0300	0.2925
mkt_boston |	0.0237	0.0751	0.3200	0.7530	-0.1242	0.1716
mkt_oakland |	-0.0017	0.0993	-0.0200	0.9860	-0.1972	0.1938
mkt_la |	0.0150	0.0798	0.1900	0.8510	-0.1421	0.1722
mkt_orange |	-0.0525	0.0793	-0.6600	0.5090	-0.2087	0.1037
mkt_sacram~o |	0.0491	0.1239	0.4000	0.6920	-0.1948	0.2929
mkt_san_de~o |	0.0119	0.1203	0.1000	0.9210	-0.2249	0.2487
mkt_san_fr~o |	-0.0155	0.0854	-0.1800	0.8560	-0.1837	0.1527
mkt_san_jose |	0.0855	0.0821	1.0400	0.2990	-0.0762	0.2472
mkt_seattle |	0.0132	0.0825	0.1600	0.8730	-0.1491	0.1756
_cons |	1.6402	0.0798	20.5500	0.0000	1.4831	1.7973

Dependant variable – Respondent 30

. regress ln_r30 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	SS	df	MS
Model |	16.41	16	1.26
Residual |	36.41	279	0.13
Total |	52.83	295	0.18

Observations	**296**
F(16, 279)	7.86
Prob F	0
R-squared	0.3107
Adj R-square	**0.2712**
Root MSE	0.36127

ln_r30 |	Coef.	Std. Err	. t	P|t|	[95% Conf.	Interval]
noi_sf |	0.0010	0.0022	0.4400	0.6620	-0.0034	0.0054
day_employ~t |	0.0000	0.0000	0.8400	0.4030	0.0000	0.0000
class_a |	-0.0172	0.0602	-0.2900	0.7750	-0.1357	0.1013
total_sf |	0.0000	0.0000	3.8100	0.0000	0.0000	0.0000
_1996_2000 |	0.4835	0.0794	6.0900	0.0000	0.3271	0.6398
_1982_1995 |	0.1886	0.0516	3.6600	0.0000	0.0871	0.2902
mkt_atlanta |	-0.1726	0.1001	-1.7200	0.0860	-0.3696	0.0244
mkt_boston |	-0.0005	0.0918	-0.0100	0.9960	-0.1812	0.1802
mkt_oakland |	-0.0268	0.1213	-0.2200	0.8250	-0.2656	0.2120
mkt_la |	0.0321	0.0975	0.3300	0.7430	-0.1599	0.2240
mkt_orange |	-0.1721	0.0969	-1.7800	0.0770	-0.3629	0.0186
mkt_sacram~o |	-0.1062	0.1513	-0.7000	0.4830	-0.4041	0.1917
mkt_san_de~o |	0.2341	0.1470	1.5900	0.1120	-0.0551	0.5234
mkt_san_fr~o |	-0.0162	0.1044	-0.1600	0.8770	-0.2216	0.1892
mkt_san_jose |	-0.1564	0.1003	-1.5600	0.1200	-0.3539	0.0410
mkt_seattle |	-0.2806	0.1007	-2.7900	0.0060	-0.4789	-0.0823
_cons |	1.3585	0.0975	13.9300	0.0000	1.1665	1.5504

Dependant variable – Respondent 31

. regress ln_r31 noi_sfday_employment class_a total_sf _1996_2000 _1982_1995mkt_atlant t_boston mkt_oakland mkt_la mkt_orange mkt_sacramento mkt_san_deigomkt_san_f isco mkt_san_jose mkt_seattle

Source |	**SS**	**df**	**MS**
Model |	6.85	16	0.43
Residual |	28.55	279	0.12
Total |	35.40	295	0.12

Observations	**296**
F(16, 279)	4.18
Prob F	0
R-squared	0.1935
Adj R-square	**0.1472**
Root MSE	0.31989

ln_r31 |	**Coef.**	**Std. Err**	**. t**	**P|t|**	**[95% Conf.**	**Interval]**
noi_sf |	-0.0016	0.0020	-0.8000	0.4240	-0.0055	0.0023
day_employ~t |	0.0000	0.0000	-0.3500	0.7230	0.0000	0.0000
class_a |	-0.0268	0.0533	-0.5000	0.6150	-0.1317	0.0781
total_sf |	0.0000	0.0000	3.2600	0.0010	0.0000	0.0000
_1996_2000 |	-0.0760	0.0703	-1.0800	0.2810	-0.2144	0.0624
_1982_1995 |	0.0432	0.0457	0.9500	0.3450	-0.0467	0.1331
mkt_atlanta |	-0.1776	0.0886	-2.0000	0.0460	-0.3520	-0.0032
mkt_boston |	0.0030	0.0813	0.0400	0.9710	-0.1570	0.1630
mkt_oakland |	0.1089	0.1074	1.0100	0.3120	-0.1026	0.3203
mkt_la |	0.0763	0.0863	0.8800	0.3780	-0.0937	0.2462
mkt_orange |	-0.1775	0.0858	-2.0700	0.0400	-0.3464	-0.0086
mkt_sacram~o |	-0.0976	0.1340	-0.7300	0.4670	-0.3614	0.1662
mkt_san_de~o |	-0.3369	0.1301	-2.5900	0.0100	-0.5930	-0.0807
mkt_san_fr~o |	-0.1542	0.0924	-1.6700	0.0960	-0.3361	0.0277
mkt_san_jose |	-0.1662	0.0888	-1.8700	0.0620	-0.3411	0.0086
mkt_seattle |	-0.1899	0.0892	-2.1300	0.0340	-0.3654	-0.0143
_cons |	1.7672	0.0863	20.4700	0.0000	1.5973	1.9371

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