Becoming a Target Market

Abstract. **Framed in a quadrant model, the data sources that analysts use to predict the performance of core property types for the major metropolitan areas in the United States are reviewed. The hypothesis is that forecasters rely on information from the economic base, the property inventory and financial performance quadrants to generate forecasts. For each core property type, analysts are rather homogeneous in grouping metropolitan areas from best to worst. However, the property type determines what sets of economic, social, inventory and market information are used. The only consistent forecast factor used across all property types appears to be economic growth.**

Introduction

Real estate investors and their advisers use a wide array of informational and analytical techniques when assessing the investment potential of the sixty major real estate markets in the United States. The complexity of the information spectrum can be illustrated by a quadrant model of multidimensional diversification parameters and risk assessment hurdles. Components include: (1) financial investment vehicles; (2) core property types (inventory modules); (3) geo-economic factors; and market cycles and performance measures (see Exhibit 1).

This study examines the use of and reliance on various information sets provided by data vendors who publish market assessments and rank metropolitan areas by property type for investment potential. As real estate becomes more institutionalized and subject to public review, these macro-market assessments regularly, guide investment activity and help underwriters to assess risk (especially the debt risk). This study does not attempt to ascertain how well the vendors predict the future; rather, it focuses on what information real estate researchers rely on in making their predictions.

To understand how rankings are derived, this review includes: (1) financial measures and indices for real estate investment vehicles; (2) sources of data and the techniques used to measure changes and momentum in the inventories of core property types;

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Exhibit 1
Quadrant Model for Risk Assessment

Financial Investment Vehicles	Core Property Types (Inventory Modules)
Geo-Economic Factors	Performance Measures and Market Cycles

(3) how real estate researchers have grouped metropolitan areas by their economic-based characteristics and what indicators are used to analyze and project economic growth within a market; and (4) performance measures and indices used in forecasting the near-term investment potential for major markets by core property types.

Data for a property type in a specific market will vary according to the vendor. The analyst's predictions, in part, also depend on the vendor used to acquire data. The ranking of markets for each property type by the major data vendors have been decomposed through clustering and discriminant analysis based on z-scored data for: (1) the financial returns for each property type for each metropolitan area; (2) the economic base of each market; (3) the inventory of each property type in each market; and the near-term forecast for each property type within each market. Clustering and the subsequent discriminant analysis highlight the uniqueness of each market. This outcome cannot be determined through additive or multiplicative index approaches.

Classification and Information Dimensions

As an asset class, investments in income-producing real estate are heterogeneous, a characteristic allowing investors to diversify their property holdings across a multitude of decision-making dimensions. Exhibit 1 summarizes the four dimensions. This section describes these four dimensions—levels—of the quadrant model as depicted in Exhibit 1. These four levels are: (1) Financial Investment Vehicles (Exhibit 2); (2)

Exhibit 2
Financial Investment Vehicles

Private Equity
Direct Investment by:

Pension Funds
Foreign Investors
Individuals
Private REITs

Public Equity

REITs
RELPs
REOCs

Private Debt
Mortgages by:

Pension Funds
Life Insurance Companies
Commercial Banks

Public Debt

CMBS
Mortgage REITs

Exhibit 3
Core Property Types (Inventory Modules)

Apartment	**Retail**
Low-rise	Neighborhood and community shopping centers
High-rise, elevator	Regional center
Garden type	Power center
	Fashion/Specialty center
	Super regional center
	Theme/Festival center
	Outlet center
Industrial	**Office**
Warehouse/Distribution	Low-rise
Manufacturing	Mid-rise
R&D/Flex space	High-rise
Office Showroom	(Class A, Class B, CBD, Suburban)
Research & Development	

Source: Real Estate Information Standards, 1997.

Core Property Types (Exhibit 3); (3) Geo-Economic Factors (Exhibit 4); and (4) Performance Measures and Market Cycles (Exhibit 5).

Each level of the model emphasizes information sets and analytical techniques for explaining the behavior of real estate investment activity. Over the years, the various vendors and analysts have collected information to analyze the past, present and future activity of real estate markets and property types.

Financial Investment Vehicles

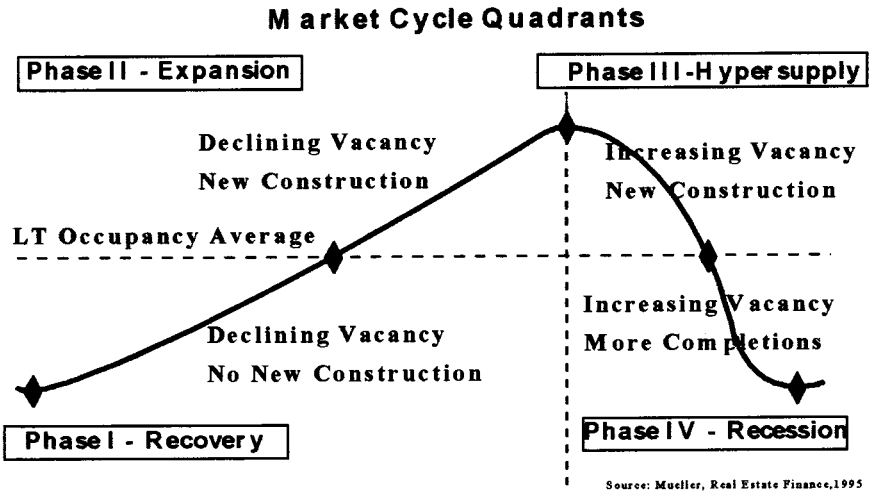
Real estate has always been viewed as an alternative to financial assets. Investing in real estate has evolved from primarily private equity ownership with private mortgage

Exhibit 4
Geo-Economic Factors

Large, Non-diversified	**Large, Diversified**
Washington, DC	Chicago, IL
Employment: 2,421,000	Employment: 3,975,000
Diversity: 0.44	Diversity: 0.77
Small, Non-diversified	**Small, Diversified**
Richmond-Petersburg, VA	Albuquerque, NM
Employment: 509,000	Employment: 335,000
Diversity: 0.43	Diversity: 0.71

Note: Metropolitan area size is measured by total employment. Economic base diversification is measured by the Industrial Diversity Index. Data provided by Regional Financial Associates, Inc.

Exhibit 5
Market Cycles



Source: Glenn Mueller, *Real Estate Market Cycles Monitor*, Legg Mason Wood, Walker, Inc. February 1998.

financing to the quadrants of investing: private equity ownership, public institutional equity investment (within a portfolio construct) private mortgage financing and public debt financing (see Exhibit 2). In recent years, real estate analysis has evolved from primarily a micro-market, deal-by-deal study to an institutional portfolio management paradigm.

The mortgage underwriting data of the American Council of Life Insurers (ACLI), the various return series of the National Council of Real Estate Investment Fiduciaries (NCREIF), various indices for the real estate investment trusts, sporadic investment house reports and federal agencies' data provide the performance indicators for the vehicles. The ACLI and NCREIF cover the underwriting and investment returns of the core property types at the metropolitan level. However, the lack of a sufficient sample size for all sixty major metropolitan areas for each property type precludes the use of that data for this study.

Using NCREIF data, Hartzell, Hekman and Miles (1986) showed modern portfolio theory (MPT) could be used when investing in real estate. Assuming the larger institutional investors have sufficient interest and appetite for real estate assets, Hudson-Wilson (1995a,b, 1996) has suggested that real estate should be treated like stocks and that efficient portfolios of real estate equity and debt could be amassed for investors with different risk utilities. MPT has been widely used and cited in the real estate industry. For example, Property & Portfolio Research (PPR) routinely tracks performance of four property types (office, retail, warehouse and apartments) in sixty U.S. metropolitan areas to produce their Derived Market Return series. Lend Lease Real Estate Investment uses the data set for the NCREIF Property Index performance

returns to generate a Risk/Return Profile of Total Returns by DMSA and then ranks top metropolitan areas for the investment potential of the core property types in their quarterly reports.

Core Property Types

Historically, brokerage activity spawned the collection of inventory and market activity data for the core property types (see Exhibit 3). With the emergence of the three national brokerage firms (CB Richard Ellis, Cushman and Wakefield, and Grubb and Ellis) in the middle 1980s, new sets of real estate inventory data emerged. The analysis of demand and supply variables focused on vacancy rates as a major barometer of real estate market health. NCREIF's calculations for different property types further galvanized the portfolio concept and the uniqueness of the core property types. The core property types can be analyzed using proprietary databases for the different property types (apartments, office, retail, warehouse/industrial and hotel) available from F. W. Dodge Real Estate Analysis and Planning Service (REAPS); the REIS Reports, Inc., New York; CB Richard Ellis/Torto Wheaton Research, Boston; Landauer Associates, New York (in association with the Society of Industrial and Office Realtors); ONCOR International; and Cushman and Wakefield's Site Solutions.

This study uses the square footage of occupied space as the inventory standard. Square footage of occupied space is analogous to employment data for commercial real estate space users (office, industrial/warehouse and retail). Changes in occupied space can be compared to changes in specific Standard Industrial Classification (SIC) employment groups.

Shilton and Tandy (1997) have shown the wide variation in the inventory data generated by the various vendors. This disparity was recognized by testing various data sources. Inventory variable estimates were obtained from the following:

Data Vendors	*Variables*
CB Richard Ellis/Torto Wheaton	Total Square Footage
Cushman & Wakefield—Site Solutions	Rank Total Sq. Ft.
F. W. Dodge/REAPS	Vacant Space (sq. ft.)
Landauer Associates—SIOR Comparative Statistics	Occupied Space (sq. ft.)
ONCOR International	Construction Completions (sq. ft.)
REIS Reports	Absorption (sq. ft.)
	Vacancy Rate (%)
	Rank Vacancy Rate
	Ratio Completions/Absorption
	Supply Percent:Completions/Total Sq. Ft.
	Demand Percent:Absorption/Occupied Space
	Effective Rental Rate ($ per sq. ft. per annum)

Geo-Economic Factors

Recent economic base studies (Barro, 1991; and Barro and Sala-I-Martin, 1992) focus on the growth among metropolitan areas. Growth is a factor of the existing size of the employment base, the diversity of the industrial mix and the cost of doing business. Analysts have used different approaches to classifying metropolitan areas for comparative market analysis. Exhibit 4 illustrates the Barro approach to metropolitan area analysis. Metropolitan areas can be grouped by size and the degree of their industrial diversity.

The Geo-Economic dimension has been the subject of a progression of geographic and/or economic-based classification schemes over the past ten years. Researchers were seeking the most effective locational method for diversifying real estate portfolios. This search for a set of geo-economic factors by which real estate investments could be tested for the degree of diversification has been likened to the search for the Holy Grail (Ziering and Hess, 1995).

The first search party consisted of real estate researchers at Salomon Brothers, Inc. in New York. They developed a geographic categorization of regional sets of metropolitan areas. The second group was formed at Prudential Real Estate Investors. Mueller (1993) examined diversifying the portfolio by economic base factors using the nine SIC Code divisions and a set of metropolitan areas where the property investments were located. The Prudential set of metropolitan areas does not completely mesh with the top sixty areas used in this study.

The third party set off in 1995, again at Prudential Real Estate Investors, where Ziering and Hess (1995) promulgated the Renaissance Economic Diversification model. This model uses a broad-based socioeconomic approach in defining market groups, following a concept set forth earlier by Miles (1989). Meanwhile, Wurtzebach (while at Heitman Capital Management) and Giliberto (while at Lehman Brothers) had used ''economic concentration'' categories derived from the earlier Salomon and Prudential studies in their published market analyses.

These studies clearly demonstrate that metropolitan areas in the U.S. have distinctive geo-economic characteristics. These variances set them apart from other areas within their region, but group widely dispersed areas having quite similar characteristics.

Metropolitan-level data for real estate markets in the geo-economic dimension were compiled from Regional Financial Associates (RFA) data plus the LaSalle Advisors' Regional Economic Growth Index. RFA is a leading information provider about the economic conditions of metropolitan areas. RFA publishes a full compendium of economic and business data that includes data sets for Total Employment, Industry Diversity and Cost of Doing Business, which is used in this study. While there are numerous other governmental and private sources for economic and business data, the RFA data have been frequently cited and used by real estate entities, such as CB Richard Ellis/Torto Wheaton, Heitman Research, REIS Reports and others.

LaSalle Advisors has developed a proprietary database, the REGI. The index is calculated each quarter to provide a leading indicator of economic strength in 112 U.S. metropolitan areas, including the sixty markets in this study. The index is based on employment and population growth, as well as momentum and risk factors including volatility, diversity and business costs. The REGI was created in the first quarter of 1995 and is published in LaSalle's quarterly report, *Market Watch.*

Selecting the Metropolitan Areas

Many information resources were reviewed to determine which metropolitan areas should comprise the first- and second-tier real estate markets in this study (see Exhibit 6). The purpose of the review was to establish the frequency with which each metropolitan area appeared in the various data sets. The final number of areas was set at sixty. After sixty, real estate data (for smaller metropolitan areas) became very sparse. The frequency of appearance in the selected information sources for the areas in this study has remained relatively consistent during the 1990s.

Market Cycles

The lack of long-term time-series data for each property type within each market area has obscured the occasional volatile nature of real estate on the metropolitan level. Not until the dramatic downturn of the late 1980s did the discussion about the cyclical nature of real estate markets arise. Phyrr, Born and Robinson (1996) summarize the emerging literature and evolution of models used to depict the various phases of the economic and business cycles of metropolitan areas to reveal the aberrations among the market cycles of the different property types. Gyourko and Keim (1992) trace the lags and leads of real estate stocks and the general stock market and the economy. Mueller (1998) models a quarterly depiction of real estate market cycles for the core property types (see Exhibit 5). Other commentators, such as Kelly (1997), have presented alternative views about stages of the real estate cycle.

Performance Measures and Real Estate Cycles

Over the past twenty years, the types and quantity of real estate and real estate-related data about markets and the performance of real estate has increased dramatically. The following were selected because of their comprehensive evaluations of the major real estate markets.

CB Richard Ellis/National Real Estate Index, San Francisco, Market Score. The rating scores presented in this quarterly publication are drawn from a proprietary model for analyzing the real estate investment potential in sixty-six metropolitan markets. It evaluates the potential performance of Class A, CBD and suburban office, industrial (warehouse), unenclosed shopping centers and apartment properties for a two-year horizon. The investment potential estimates are presented as a continuum:

Exhibit 6
Sixty U.S. Metropolitan Areas in Nine Geographic Regions

First Tier	Second Tier
Northeast Atlantic	Hartford, CT
Boston, MA	
Middlesex-Central NJ	
Newark-Northern NJ	
Nassau-Suffolk, NY	
New York, NY	
Mid-Atlantic	
Washington, DC	Norfolk-Virginia Beach–Newport News, VA
Baltimore, MD	Richmond-Petersburg, VA
Philadelphia, PA-NJ	
South Atlantic	
Atlanta, GA	Charlotte-Gastonia-Rock Hill, NC
	Greensboro-Winston-Salem-High Point, NC
	Raleigh-Durham-Chapel Hill, NC
	Greenville-Spartanburg-Anderson, SC
Florida	
Miami, FL	Fort Lauderdale, FL
Tampa-St. Petersburg, FL	Jacksonville, FL
	Orlando, FL
	West Palm Beach-Boca Raton, FL
Mid-South	Birmingham, AL
	Memphis, TN
	Nashville, TN
Midwest–Great Lakes	
Chicago, IL	Cincinnati, OH
Cleveland-Lorain-Elryia, OH	Columbus, OH
Detroit, MI	Indianapolis, IN
Pittsburgh, PA	
Midwest – Plains	
Minneapolis-St. Paul, MN	Milwaukee-Waukesha, WI
Kansas City, MO-KS	
St. Louis, MO-IL	
Oil Patch	
Denver, CO	New Orleans, LA
Dallas, TX	Oklahoma City, OK
Houston, TX	Austin-San Marcos, TX
	Fort Worth-Arlington, TX
	San Antonio, TX
Far West – South	
Phoenix-Mesa, AZ	Tucson, AZ
Los Angeles-Long Beach, CA	Riverside-San Bernardino, CA
Orange County, CA	Honolulu, HI
San Diego, CA	Las Vegas, NV
	Albuquerque, NM
Far West–North	
Oakland, CA	Sacramento, CA
San Francisco, CA	Salt Lake City-Ogden, UT
San Jose, CA	
Portland-Vancouver, OR-WA	
Seattle-Bellevue-Everett, WA	

Rating	*Score*
Extraordinary	95+
Excellent	90–94
Good	80–89
Fair	70–79
Poor	60–69
Speculative	59 and below

All sixty-six markets are analyzed, scored and ranked for each quarter.

Landauer Associates, New York, Real Estate Market Forecast. The Landauer Market Quality Ratings (MQRs), which first appeared in 1993, evaluate sixty office markets with scores from one (the best) to seven (the worst). The sample for retail markets also numbers sixty. MQRs are available only for the warehouse/distribution market, not total industrial, but Landauer calculates ''Power Ratings'' for the top ten markets for research and development, light assembly and warehouse/distribution in their annual report. Multifamily markets (fifty-eight) also receive MQR designations with Landauer rating apartments according to their Consolidated Indicators Scale.

Legg Mason Wood Walker Real Estate Research Group, Baltimore, MD, Real Estate Market Cycle Monitor. Publication of this ''executive summary'' began in January 1997 with data for the Third Quarter 1996. It is a continuation of the real estate market analyses of Mueller. The metropolitan area's position in the cycle is presented graphically for the four core property types. The prime, or ''best pick'' position, is on the ascending side of the cycle.

Property & Portfolio Research, Boston. PPR, working with large investors, takes a quantitative, capital asset pricing model approach to real estate investment and applies modern financial theory to the design of appropriate real estate portfolios. PPR models the performance of private equity, public equity, private debt and public debt and the core property types. The Derived Market Returns (DMR) series are the primary forecasting indicators in the PPR reports (Stimpson, 1997).

REIS Reports, New York. On their web site (www.reisreports.com) this firm provides (as of January 1999) forecasts for four core property types: office, retail, apartment and industrial, with analyses of average rent growth and vacancy rates for a five-year projection period.

Research Design

Investors often take a ''bottom-up'' approach to obtain information on specific property types in specific metropolitan areas and a ''top-down'' approach in which they screen metropolitan areas for further investigation (the risk assessment hurdles). Therefore, the real estate investor seeks advice and information from a group of ''experts'' on the investment potential of a core property type and/or a specific metropolitan area. The problem encountered is that the experts frequently do not agree on which is the best and the worst property type or the best and worst metropolitan area. The information asymmetry in the data sets and the variance of expertise in analyzing the data cause the divergence in expert opinions.

Investors face an ''aggregation problem'' of expert predictions when trying to sort out expert opinions to determine who may be the ''true expert'' (Myung, Ramamoorti and Bailey, 1996). This study presents the first phase in studying historical and present patterns, as well as future predictions. Because of the lack of a comprehensive historical database of predictions (forecasts), it is not possible to assess who was best foreseeing what would happen. The focus of this phase is to discern the types of information used and the divergence or homogeneity of opinions.

The aggregation approach assumes that for each property type, forecasters incorporate for each metropolitan area what is occurring in the economic base of the area and what is occurring in the inventory of a core property type in that area. As a result of assessing the economic base and the inventory variables, the analyst then predicts the expected performance for that property type.

Numerous trials of various data sets and indices for the economic, the inventory and performance indicators were conducted to set up the risk assessment hurdles. The final set of economic-based characteristics used include: (1) Lehman Brothers' three-year employment growth; (2) RFA's Cost of Doing Business Index; (3) La Salle's REGI of long-term economic performance for metropolitan area; and (4) the RFA Industrial Diversity Index.

For each property type within each metropolitan area, the final inventory characteristics used include: (1) the reported vacancy rate (Equation (1)); (2) property location quotient that measures the proportion of a core property type of the entire commercial property inventory (Equation (1)); and (3) a ratio of expected new construction against previous construction (Equation (2)).

$$\frac{\text{local specific property type supply}}{\text{entire local commercial property supply}} \div \frac{\text{specific property type supply in all areas}}{\text{total commercial real estate supply in all areas}} \tag{1}$$

$$\frac{\text{most recent three years of construction}}{\text{forecast of next three years of construction}} \tag{2}$$

For each property type within a metropolitan area the performance predictions from the following are used: (1) the CB Richard Ellis/National Real Estate Index's *Market Score* rating; (2) the Landauer MQR; (3) a numerical adaptation of the placement of the property/metro area along Mueller's real estate cycle model; and (4) PPR's Derived Market Return estimates.

Interpreting the Predictions

Consider the distribution of the predictions for a property type in a metropolitan area. The possible outcomes among a group of experts could be: (1) all property types in

all areas score the same; the implication being that a national market equilibrium exists; (2) the final score from best to worst take on a normal distribution with the majority (68%) falling within plus or minus one standard deviation of the mean; and (3) an unevenness in the scores; clusters of scores occur within the steps of the ranking.

Little in the current literature suggests that real estate markets in the U.S. have reached a national equilibrium. Normal distributions of scores will likely occur if axiomatic aggregation techniques are used (Myung, Ramamoorti and Bailey, 1996), but this approach rarely has been justified or explicitly discussed. Simple weighting of scores and totaling them or multiplying the scores ignores the entropy of information content in these predictions. In contrast, expert predictions are a function of the information set and the sensitivity of experts to the predictions of their peers. In the entropy model of expert predictions, a group of associated opinions will cluster about each random event (the investment return of a property type in a metropolitan area). These opinions will not be normally distributed because of the implied covariance of either information content and/or peer association.

Accordingly, the hypothesis is that there are clusters in the rankings for the performance of core property types (based on correlations with economic base and inventory variables). Given the lack of economic equilibrium between metropolitan areas and the uniqueness of each property market, clusters of areas as to their economic base and to the property market characteristics, should be found. The discriminant analysis will be used to test whether significant statistical differences will be found among these clusters.

Clustering using Standardized Z-Scores

In the past, clustering has been used for choosing the appropriate sample of houses for hedonic regression analysis (Graaskamp, 1979) to grouping metropolitan areas for investment (Goetzmann and Wachter, 1995). Given a set of variables, clustering starts with a case and finds the next case that is closest in Euclidean distance for each variable. The clustering continues until the specified sets of clusters are formed. Each cluster has its own unique mean for each variable. If the clusters are statistically different, the cluster means of each variable will be statistically different using analysis of variance (ANOVA).

Caution, however, must be exercised in setting up the data. If variables of different units and magnitude are used, such as price per square foot and vacancy rates, the variables of a larger magnitude will dominate. Accordingly, data used for a clustering routine should be standardized (Anderberg, 1973). Standardization equally weights the impact of each variable and it's associated distance to a cluster center.

The longstanding usage of geographic divisions of the ACLI census-based geographic units set the clustering to nine groups. The data sets were standardized and appropriate reciprocals were taken to force most of the data to run from ''left to right, bad to good,'' in the standardized sample distribution.

Procedure

From the standardized data, the following three sets of clusters were generated: (1) ecobase—the economic-based clusters for the sixty metropolitan areas, representing the geo-economic dimension; (2) inventory—the inventory clusters of metropolitan areas for each property type representing the core property type dimension; and (3) forecast rankings, the 1997 performance measure of metropolitan areas for each property type, representing the market cycle dimension.

Each set of clusters are grouped from best to worst; cluster one represents the best of the metropolitan areas, cluster nine is the worst.

An initial correlation analysis highlights those economic-based and core-property type variables that correlate with the resulting performance cluster ranks. ANOVA determines whether the clusters are significantly different and whether obvious differences occurred among the cluster means for each variable. Discriminant analysis determines the degree of the significance of the variables that were correlated with the final cluster rankings for each property type.

The hypothesis is that a high scoring, favorably ranked economic base metropolitan area that had a high scoring, favorably ranked demand/supply balance would lead to a high scoring, favorable performance forecast. The test is whether the rankings in each of the categories align.

The Results

This study found that the investment opportunities should not be targeted using geographic regions or divisions, but rather by metropolitan areas and property types. The property types in each metropolitan area vary significantly in their investment rankings.

Ecobase Clusters

As Exhibit 7 shows, the underlying growth momentum and business attractiveness of metropolitan area varies significantly. Cluster one is the highest growth/attractiveness cluster and cluster nine is the worst growth. The larger the metropolitan area, the lower the growth rate. The clustering illustrates, once again, the dilemma of trying to compare percentage growth and absolute growth. In the forecasting clusters, percentage growth is a major component in the market forecasts.

For each group, the standard deviations were taken for each of the variables. Only small variations occurred among the standard deviations of the clusters, an observation that suggests that clustering captures the uniqueness of each group. Standard deviations were not computed for clusters of fewer than three metropolitan areas.

Inventory Clusters

The Office Inventory Clusters (Exhibit 8) can be strongly differentiated on the basis of their property location quotient (Equation (1)) and vacancy rate. However, the

Exhibit 7
Ecobase Clusters

Area	Cluster	Total Employment	Lehman 3-Year Growth	Cost of Business	Industrial Dive
Albuquerque, NM	1	335.6	2.61	91.56	0.71
Austin, TX	1	541.3	3.91	96.91	0.58
Ft. Lauderdale, FL	1	607.6	3.75	100.94	0.71
Jacksonville, FL	1	492.4	3.76	100.20	0.70
Minn./St. Paul, MN	1	1568.4	2.41	104.00	0.72
Oklahoma City, OK	1	490.6	2.82	93.40	0.78
Orlando, FL	1	730.4	5.10	92.80	0.64
Portland, OR-WA	1	875.9	4.40	98.40	0.84
Raleigh-Durham, NC	1	565.1	3.57	96.30	0.65
Riverside-SB, CA	1	796.0	3.79	96.30	0.81
Sacramento, CA	1	606.1	2.80	97.00	0.79
Salt Lake City, UT	1	646.1	4.96	92.20	0.77
San Antonio, TX	1	638.8	2.87	91.90	0.73
San Diego, CA	1	991.0	2.34	96.30	0.64
Seattle, WA	1	1226.5	4.02	101.40	0.48
St. Louis, MO	1	1258.9	1.65	87.60	0.77
Tampa Bay, FL	1	1024.5	3.36	91.30	0.76
Group Std. Dev.			0.91	4.22	0.09
Atlanta, GA	2	1906.4	4.08	105.69	0.84
Boston, MA	2	2933.7	2.35	116.03	0.75
Chicago, IL	2	3975.3	1.72	110.23	0.77
Dallas, TX	2	1659.4	3.99	102.22	0.76
Denver, CO	2	1007.6	2.82	103.31	0.71
Phoenix-Mesa, AZ	2	1276.8	6.84	106.60	0.69
Group Std. Dev.			1.66	4.65	0.05
Las Vegas, NV	3	592.1	7.62	89.90	0.22
Charlotte, NC	4	722.5	2.31	97.40	0.48
Fort Worth, TX	4	676.9	3.54	94.22	0.41
Greensboro, NC	4	609.7	1.31	91.00	0.31
Greenville, SC	4	451.7	2.03	98.89	0.26

Exhibit 7 (continued)
Ecobase Clusters

Area	Cluster	Total Employment	Lehman 3-Year Growth	Cost of Business	Industrial Dive
New Orleans, LA	4	601.3	1.62	82.80	0.56
Norfolk, VA	4	630.7	1.90	88.40	0.34
Richmond, VA	4	509.6	1.34	85.20	0.43
Tucson, AZ	4	309.5	1.60	98.30	0.52
Group Std. Dev.			0.68	5.77	0.10
Baltimore, MD	5	1133.8	0.85	99.63	0.81
Birmingham, AL	5	446.6	1.95	97.18	0.69
Cincinnati, OH	5	817.4	2.17	99.70	0.71
Cleveland, OH	5	1117.0	1.82	103.55	0.67
Columbus, OH	5	796.6	2.62	99.34	0.73
Indianapolis, IN	5	802.9	2.10	98.20	0.76
Kansas City, MO	5	889.0	2.20	100.50	0.66
Memphis, TN	5	540.5	2.32	99.00	0.62
Miami, FL	5	951.0	1.92	101.10	0.65
Middlesex, NJ	5	1130.4	2.20	104.00	0.60
Milwaukee, WI	5	810.1	1.43	98.90	0.60
Nashville, TN	5	608.4	2.27	102.50	0.72
Nassau-Suffolk, NY	5	1105.2	1.24	116.90	0.76
Newark, NJ	5	1794.5	0.77	106.90	0.55
Oakland ,CA	5	912.6	2.28	105.70	0.80
Orange, CA	5	1175.8	2.68	103.30	0.71
Philadelphia, PA	5	2182.5	1.02	110.20	0.79
Pittsburgh, PA	5	1059.9	0.64	102.80	0.66
Group Std. Dev.			0.63	4.73	0.07
Hartford, CT	6	592.1	−0.80	111.69	0.22
Detroit, MI	7	2062.5	2.37	106.62	0.44
Honolulu, HI	7	404.6	2.70	120.34	0.50
San Jose, CA	7	863.6	4.82	113.40	0.26

Exhibit 7 (continued)
Ecobase Clusters

Area	Cluster	Total Employment	Lehman 3-Year Growth	Cost of Business	Industrial Dive
W. Palm Beach, FL	7	407.3	4.13	105.40	0.51
Group Std. Dev.			1.01	5.97	0.10
New York, NY	8	3839.7	0.85	142.40	0.48
San Francisco, CA	8	923.6	2.79	120.20	0.64
Washington, DC	8	2421.0	1.32	119.90	0.44
Group Std. Dev.			0.83	10.54	0.09
Houston, TX	9	1806.8	−0.17	93.50	0.56
Los Angeles, CA	9	3846.1	1.49	113.00	0.58

Exhibit 8
Office Inventory Clusters

Area	Cluster	Property Location Quotient	Past/Future Elasticity	Vacancy Rate
Birmingham, AL	1	0.990	1.574	8.7
Boston, MA	1	1.190	0.016	7.6
Nashville, TN	1	0.836	0.570	7.6
Portland, OR-WA	1	0.900	0.442	7.5
Raleigh-Durham, NC	1	1.048	0.773	8.2
San Francisco, CA	1	1.330	0.272	7.5
San Jose, CA	1	1.227	0.306	7.1
Seattle, WA	1	1.017	0.761	8.3
Charlotte, NC	2	0.843	0.485	9.7
Columbus, OH	2	0.753	0.851	10.3
Denver, CO	2	1.180	0.610	11.1
Ft. Lauderdale, FL	2	0.694	0.624	10.6
Las Vegas, NV	2	0.678	0.532	10.5
Minn/St.Paul, MN	2	0.963	0.424	10.4
Orlando, FL	2	0.796	0.779	10.4
Pittsburgh, PA	2	1.029	0.361	11.6
Richmond, VA	2	0.892	0.749	11.4
Sacramento, CA	2	0.950	0.287	10.1
Salt Lake City, UT	2	0.784	0.750	9.5
Cincinnati, OH	3	0.855	0.188	11.8
Atlanta, GA	4	0.881	0.818	12.3
Austin, TX	4	1.175	0.634	13.1
Baltimore MD	4	0.970	0.765	14.3
Chicago IL	4	1.040	0.495	15.0
Greensboro, NC	4	0.830	0.919	12.7
Indianapolis, IN	4	0.890	0.442	13.4
Jacksonville, FL	4	0.863	0.746	13.6
Kansas City, MO	4	0.960	0.744	12.3
Norfolk, VA	4	0.830	0.777	14.3
Oakland, CA	4	1.090	1.366	13.5
Philadelphia, PA	4	1.059	0.434	14.0
Phoenix-Mesa, AZ	4	0.847	0.304	13.1
San Antonio, TX	4	0.880	0.384	14.5
St. Louis, MO	4	0.994	0.797	13.4
W. Palm Beach, FL	4	0.923	0.467	12.3
Washington, DC	4	1.518	1.066	12.0
Detroit, MI	5	1.030	0.119	14.3
Dallas, TX	6	1.018	0.601	18.0
Fort Worth, TX	6	0.708	0.500	18.1
Greenville, SC	6	0.746	1.037	17.4
Honolulu, HI	6	0.997	na	18.0
Los Angeles, CA	6	0.996	1.222	19.3
Miami, FL	6	0.766	0.882	17.7
Oklahoma City, OK	6	0.848	0.390	17.8
Orange County, CA	6	0.845	1.286	17.2
Cleveland, OH	7	0.823	0.823	16.5
Nassau-Suffolk, NY	7	0.991	0.000	15.6
New York, NY	7	1.360	−0.013	14.8

Exhibit 8 (continued)
Office Inventory Clusters

Area	Cluster	Property Location Quotient	Past/Future Elasticity	Vacancy Rate
Newark, NJ	7	1.265	−0.096	16.7
San Diego, CA	7	0.981	1.382	16.5
Tampa Bay, FL	7	0.814	1.649	16.3
Houston, TX	8	0.972	1.075	22.0
Milwaukee, WI	8	0.843	13.000	20.9
New Orleans, LA	8	0.815	2.813	23.1
Riverside-SB, CA	8	0.464	4.200	24.0
Hartford, CT	9	1.264	1.193	30.8

impact of future supply as opposed to past supply (Equation (2)) is not as clear. Cluster rankings were similarly derived for retail and warehouse/industrial.

Forecast Performance

The forecasts of performance measures cluster for office, retail and warehouse markets for 1997 are presented in Exhibits 9–11, respectively. They present a picture for the major forecasters for 1997. The essence of this study, however, is contained in the Exhibits 12 and 13 that illustrate the ''rolling'' dynamics of market selection. Exhibit 12 illustrates the consensus about investment appeal by property type. The number of metropolitan areas in each cluster and the relative ranking of the clusters tells a story of the diversity of investment preferences across property types.

Offices. Ten metropolitan areas clustered at the top rank, but only nine for retail and two for warehousing. There was strong sentiment for offices in clusters two through four. In contrast, only one group of cities (cluster 9) was viewed as poor, with four other metropolitan areas vying for a lower spot among the clusters.

Retailing. One group of nine metropolitan areas in cluster one won the approval of forecasters, but then the bulk of the sentiment about retailing was in the middle categories—neither spectacular nor poor.

Warehousing. Warehousing was modestly good (clusters two through five) or poor (clusters seven through nine).

The standard deviation of each cluster and the averages of the standard deviation are given to present the relative homogeneity of each cluster. In addition, ANOVA was performed on each set of forecast clusters for each property type. Each cluster was significantly different statistically from the other clusters for that property type.

Information Sets Influencing Forecasts

For each property type, each metropolitan area was coded as to its cluster group. The supporting geo-economic data and inventory data were aligned for that metropolitan

Exhibit 9
Forecast Performance for Office Markets—1997

Area	Cluster	SCRCBD	SCRESUE	LANMQR	Cycle
Boston, MA	1	95	93	4	6
Ft. Lauderdale, FL	1	90	90	2	5
Nashville, TN	1	83	94	3	6
Orlando, FL	1	91	90	2	6
Phoenix-Mesa, AZ	1	82	91	2	5
Portland, OR-WA	1	93	93	2	8
Salt Lake City, UT	1	91	91	3	8
San Francisco, CA	1	94	94	4	5
San Jose, CA	1	91	93	3	5
Seattle, WA	1	94	89	3	5
Charlotte, NC	2	87	84	3	7
Orange County, CA	2	91	81	4	5
Riverside-SB, CA	2	73	79	4	5
Sacramento, CA	2	86	85	1	6
Atlanta, GA	3	79	84	3	6
Austin, TX	3	81	89	3	7
Columbus, OH	3	92	85	5	8
Denver, CO	3	82	87	3	6
Fort Worth, TX	3	63	87	3	4
Tampa Bay, FL	3	73	87	3	6
W. Palm Beach, FL	3	68	88	3	6
Dallas, TX	4	63	87	3	3
Indianapolis, IN	4	74	88	3	4
Jacksonville, FL	4	79	91	3	7
Kansas City, MO	4	84	93	3	6
Miami, FL	4	69	88	3	5
Nassau-Suffolk, NY	4	86	88	3	5
Oakland, CA	4	83	93	4	5
San Antonio, TX	4	73	91	3	5
San Diego, CA	4	75	89	4	5
St. Louis, MO	4	70	92	5	6
Chicago, IL	5	84	87	4	3
Cincinnati, OH	5	74	90	5	4
Houston, TX	5	77	85	4	3
Washington, DC	5	85	89	4	4
New York, NY	6	93	83	7	1
Pittsburgh, PA	6	80	84	7	2
Baltimore, MD	7	75	89	5	3
Cleveland, OH	7	75	88	7	2
Detroit, MI	7	80	92	7	4
Los Angeles, CA	7	72	87	6	1
New Orleans, LA	7	60	91	7	1
Newark, NJ	7	71	88	7	5
Norfolk, VA	7	64	90	6	4
Oklahoma City, OK	7	59	91	7	4
Philadelphia, PA	7	76	89	7	3
Hartford, CT	8	62	74	7	1
Honolulu, HI	9	62	81	5	−8

Note: PPR data was used for clustering but is not reproduced for confidentiality reasons. Missing data for Albuquerque NM, Birmingham AL, Greensboro NC, Greenville SC, Las Vegas NV, Memphis TN, Middlesex NJ, Milwaukee WI, Minneapolis MN, Raleigh-Durham NC, Richmond VA and Tucson AZ.

Exhibit 10
Forecast Performance for Retail Markets—1997

Area	Cluster	SCRRETL	LANMQR	Cycle
Dallas, TX	1	82	5	8
Ft. Lauderdale, FL	1	84	4	6
Jacksonville, FL	1	77	5	7
Phoenix-Mesa, AZ	1	82	4	7
Pittsburgh, PA	1	78	5	−2
San Antonio, TX	1	74	5	−2
Tampa Bay, FL	1	78	4	7
W. Palm Beach, FL	1	82	4	6
Washington, DC	1	81	4	7
Miami, FL	2	86	4	−1
Portland, OR-WA	2	94	4	−1
Austin, TX	3	84	5	8
Chicago, IL	3	81	4	7
Cincinnati, OH	3	80	5	−2
Columbus, OH	3	80	5	−2
Detroit, MI	3	83	5	−2
Houston, TX	3	84	4	8
Kansas City, MO	3	81	5	−2
Los Angeles, CA	3	81	5	−2
Nashville, TN	3	87	5	7
New Orleans, LA	3	81	6	6
Orlando, FL	3	80	5	−1
Riverside-SB, CA	3	77	5	−2
St. Louis, MO	3	81	4	5
Boston, MA	4	80	7	−2
Charlotte, NC	4	82	6	8
Fort Worth, TX	4	82	6	−2
Honolulu, HI	4	83	7	8
Salt Lake City, UT	4	88	6	−1
San Jose, CA	4	88	6	4
Seattle, WA	4	90	6	−2
Minn/St.Paul, MN	5	79	6	8
Oklahoma City, OK	5	80	6	7
Sacramento, CA	5	79	7	4
San Francisco, CA	5	86	6	6
Atlanta, GA	6	83	5	−4
New York, NY	6	84	6	2
Newark, NJ	6	85	6	−5
Oakland, CA	6	83	6	−3
San Diego, CA	6	82	6	−4
Baltimore, MD	7	79	6	−4
Cleveland, OH	7	76	5	−5
Denver, CO	7	80	6	−4
Indianapolis, IN	7	79	5	−5
Milwaukee, WI	7	78	6	−6
Richmond, VA	7	78	6	−4
Norfolk, VA	8	71	4	−4
Philadelphia, PA	8	75	5	−3
Hartford, CT	9	71	7	−6
Nassau-Suffolk, NY	9	75	7	−6

Exhibit 11
Forecast Performance of Warehouse Markets—1997

Area	Cluster	Score	LANMQR	Cycle
Cincinnati, OH	1	88	4	7
Nashville, TN	1	88	3	−2
Atlanta, GA	2	83	3	−1
Charlotte, NC	2	81	2	6
Chicago, IL	2	82	2	7
Dallas, TX	2	83	2	7
Denver, CO	2	84	2	6
Ft. Lauderdale, FL	2	84	2	8
Houston, TX	2	86	3	6
Jacksonville, FL	2	81	3	6
Miami, FL	2	83	3	4
Minn/St.Paul, MN	2	83	2	7
Phoenix-Mesa, AZ	2	83	3	−1
Portland, OR-WA	2	86	2	6
Riverside-SB, CA	2	83	2	7
San Antonio, TX	2	85	3	7
Austin, TX	3	84	4	−1
Cleveland, OH	3	85	5	4
Detroit, MI	3	86	4	7
Kansas City, MO	3	90	5	6
Milwaukee, WI	3	87	5	8
Oakland, CA	3	85	4	6
Salt Lake City, UT	3	85	4	7
San Francisco, CA	3	86	5	6
Fort Worth, TX	4	83	5	7
New Orleans, LA	4	80	5	5
Orange, CA	4	81	4	6
Orlando, FL	4	82	4	8
Philadelphia, PA	4	79	6	6
Richmond, VA	4	86	5	6
Sacramento, CA	4	84	4	6
San Diego, CA	4	84	4	6
Seattle, WA	4	82	4	−1
W. Palm Beach, FL	4	85	4	6
Baltimore, MD	5	77	4	5
Columbus, OH	5	80	5	4
Indianapolis, IN	5	80	3	8
Memphis, TN	5	80	4	7
Washington, DC	5	80	3	4
Boston, MA	6	83	5	4
Newark, NJ	6	84	7	3
Los Angeles, CA	7	89	3	2
Oklahoma City, OK	7	91	4	6
San Jose, CA	7	91	3	6
St. Louis, MO	7	90	3	5
Tampa Bay, FL	7	86	3	1
Hartford, CT	8	81	6	−6
Honolulu, HI	9	77	5	−6
Nassau-Suffolk, NY	9	79	7	−8
New York, NY	9	78	7	−6

Exhibit 12
Standard Deviations of Property Forecast Clusters

	Office							Retail					Warehouse		
Cluster	Number	SCRCBD	SCRESUB	PRCBD	PRSUB	LANMQR	CYCLE	Number	SCRRETL	PRCRETL	LANMQR	Cycle	Number	Score	PRCWRH
1	10	4.2	1.7	28.3	28.5	0.7	1.1	9	3.01	15.56	0.50	3.73	2	*	*
2	4	6.8	2.4	16.8	22.0	1.2	0.8	2	*	*	*	*	14	1.49	4.89
3	7	9.0	1.6	17.9	11.0	0.7	1.1	13	2.37	13.04	0.53	4.40	8	1.73	7.21
4	10	7.0	2.1	20.3	10.8	0.7	1.0	7	3.57	26.58	0.45	4.36	10	2.11	7.15
5	4	4.6	1.9	56.9	28.5	0.4	0.5	4	2.92	29.28	0.43	1.48	5	1.20	4.03
6	2	*	*	*	*	*	*	5	1.02	6.28	0.40	2.48	2	*	*
7	9	7.1	1.6	29.2	25.8	0.7	1.3	6	1.25	6.87	0.47	0.75	5	1.85	10.80
8	1	*	*	*	*	*	*	2	*	*	*	*	1	*	*
9	1	*	*	*	*	*	*	2	*	*	*	*	3	0.82	
Average		5.52	1.62	24.19	18.10	0.64	0.85		2.02	13.95	0.40	2.46		1.20	4.87

Note: Insufficient cases to determine standard deviation. Price data (PRC**) was not used for clustering purposes; presented for inf

Exhibit 13
Information Sets Influencing Market Performance Forecasts

Variable	Wilks' Lambda	*F*-Statistic	Significance
Panel A: Office Forecasts			
3-yr Growth	0.607	3.235	0.006*
Business Cost	0.756	1.618	0.150
Diversity	0.767	1.524	0.180
REGI	0.603	3.289	0.006*
Property LQ	0.758	1.597	0.157
Past/Future Sup.	0.912	0.479	0.863
Vacancy	0.392	7.765	0.000*
Panel B: Retail Forecasts			
3-yr Growth	0.675	2.465	0.028*
Business Cost	0.814	1.174	0.338
Diversity	0.802	1.269	0.286
REGI	0.768	1.546	0.172
Property LQ	0.908	0.517	0.836
Past/Future Sup.	0.686	2.349	0.035*
Vacancy	0.836	1.004	0.448
Panel C: Warehouse Forecasts			
3-yr Growth	0.678	2.379	0.034*
Business Cost	0.603	3.288	0.006*
Diversity	0.715	1.996	0.072
REGI	0.563	3.878	0.002*
Property LQ	0.636	2.861	0.013*
Past/Future Sup.	0.781	1.405	0.224
Vacancy	0.750	1.663	0.138

*Significant at the 95% confidence level.

area. Did the geo-economic data and the inventory data contribute to the cluster ranking? Discriminant analysis was applied and the resulting ANOVA statistics were derived.

Exhibit 13 illustrates that only employment growth was a common factor in influencing forecasts. Otherwise, each property type had its own set of contributing variables. Growth, the vacancy rate and the REGI were the factors influencing office forecasts. Growth and the difference between past and future supply influences the retail rankings. Growth, REGI and property LQ drove the forecasts on warehousing.

Conclusion

The major analysts in real estate incorporate a wide array of informational and analytical techniques to assess the investment potential of the sixty major real estate

markets in the U.S. The quadrant model of multidimensional diversification parameters and risk assessment hurdles illustrates the complexity of the information spectrums. These information sets guide analysts in selecting real estate investments.

Forecasters clearly distinguish between property types and among metropolitan areas in assessing the markets. A metropolitan area may be ''hot'' for office investment but ''poor'' for warehousing. The homogeneity of rankings indicates that analysts share similar opinions about how property types in many metropolitan areas will perform.

Analysts select different types of information for each property type. Employment growth data was the only variable consistently used for all three property types: office, retail and warehousing. Surprisingly, the vacancy rate was not a key variable for either retailing or warehousing. However, each of the four quadrants is part of the puzzle of future markets that the forecasters seek to solve.

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