An Analysis of Hotel Real Estate Market Dynamics

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Abstract

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After providing a conceptual analysis of national hotel cycles, metro level hotel market dynamics are examined using various measures of supply and demand volatility, and historical revenue per available room (REVPAR) performance. Cluster analysis is used to provide a more rigorous classification of hotel markets in relatively homogeneous groups. A clustering algorithm is applied to REVPAR growth across fifty-eight metro areas. Using discriminant analysis, each cluster is then linked to various economic characteristics. Five hotel market clusters are identified with differences in various employment location quotients, employment SIC categories and employment growth largely determining the cluster groupings. This analysis can be used to improve hotel portfolio diversification strategies for both real estate investment trusts and direct-side equity investors.

Introduction

Despite growing ownership interest by both direct equity investors and real estate investment trusts (REITs) in hotel real estate, there is relatively limited macroeconomic research on hotel property market dynamics. Most existing macro models of hotel demand and supply fundamentals are housed in research departments of the larger consulting firms. PricewaterhouseCoopers and F. W. Dodge/McGraw-Hill have been leaders in providing econometric forecasting models of hotel supply and demand, both at the national and regional levels. As such, much of the hotel macro-level research is proprietary with limited formal analysis by academic researchers. Moreover, many real estate researchers feel that hotels are more a management-intensive business rather than a distinct real estate asset class. Therefore, the real estate aspects of hotel investment have been largely ignored.

In this article, we provide a conceptual examination of the nature of hotel real estate, focusing on its cyclical behavior both on a national and a regional level.

In the next section, the long run national hotel real estate cycle is compared to that of the office market. The following section compares hotel market dynamics at the metro level using various measures of supply and demand volatility followed by an analysis of historical REVPAR performance. Next, cluster analysis is used to develop relatively homogeneous groupings of the metropolitan hotel markets. Subsequently, discriminant analysis is applied to link various local economic variables to the cluster groupings. Clustering of local hotel markets may potentially benefit hotel real estate portfolio managers to optimize their diversification strategies across geographies and to better evaluate regional hotel market cycles.

Real Estate Market Cycles: Empirical Evidence

The predominant focus of existing empirical research on commercial real estate market dynamics has been on office space. This is partly because office markets have the most detailed and reliable information available of all commercial property markets. Much of the research on office markets has concentrated on supply and demand modeling (Rosen, 1984), the relationship between rent levels and vacancy rates (Hekman, 1985; Shilling, Sirmans and Corgel, 1987; and Wheaton and Torto, 1994), and office market cycles (King and McCue, 1987; Wheaton, 1987; Voith and Crone, 1988; and Grenadier, 1995). For a complete review of the office market literature, see Hysom and Crawford (1997) and for a complete review of office market dynamics, see Clapp (1993).

One of the main observations regarding the dynamic behavior of office markets has been the periods of persistently high and low vacancy rates. For example, in contrast to the housing market, fluctuations in office vacancy are far more pronounced and persist for many periods. This seems to indicate that the office market does not clear and, rather, is always in a state of disequilibrium. The two standard explanations for this pattern of behavior are as follows:

- An important characteristic of real estate is that there is a substantial lag between initiation of the project and completion of construction. The construction cycle of downtown office buildings, in particular, may take two to three years. This increases the risk of real estate development since the economic environment of markets may change unexpectedly between initiation and completion of any project. If market conditions deteriorate, the newly completed space will add to the inventory of vacant space. This lag in construction has given rise to prolonged cycles of overbuilding. Vacancy rates will remain high until market conditions improve and the excess space is absorbed.
- There are substantial adjustment costs in office market lease turnovers. These include all tenant improvement costs and leasing commissions. It has been argued that lease turnover costs prevent landlords from adjusting rents automatically in view of excess vacant space. This inertia on the part of landlords is a secondary source of persistently high or low vacancy rates (see Grenadier, 1995).

Hotel real estate shares many of the characteristics observed for offices. On the supply side, hotels, especially the full-service downtown-located variety, take considerable time to plan and construct. Exhibit 1 graphs quarterly hotel and office construction starts (at seasonally adjusted annual rates). The similarity in supply cycles is quite apparent, implying that whatever drives long-run office starts is also a significant determinant of hotel construction cycles.[1] Since 1970, a span of twenty-eight years, the national hotel market has experienced only two major cycles. Wheaton and Rossoff (1997) also observe the same pattern using a different data set on hotel construction. Each of the cycles lasted roughly ten to twelve years with the duration of contractions exceeding that of expansions. Supply appears to be insensitive to the more frequent fluctuations in underlying economic fundamentals.[2] Similar to office and large regional malls, long lags exist between hotel development decisions and the actual completion of new space. By the time new completions enter the stock of space, market conditions may have changed. These lags create a large degree of risk for the developer and may be potentially responsible for some of the observed cyclical behavior in real estate markets. Similar to the office market, the lagged or slow response of hotel supply is a major cause of the lodging market real estate cycle. Historically, new hotels have been built due to either an abundance of capital or when unexpected growth in an area drives up occupancy rates, attracting lenders, developers, hotel chains and management companies to the area. Historical evidence also shows that among the major commercial property sectors, overbuilding has proven to be the greatest risk for the hotel industry.

Notable differences in long-term supply growth do exist, however, across the major commercial real estate property markets (see Exhibit 2). Among all

Exhibit 1 | U.S. Office and Hotel Construction Starts: 1970:1 – 1998:4

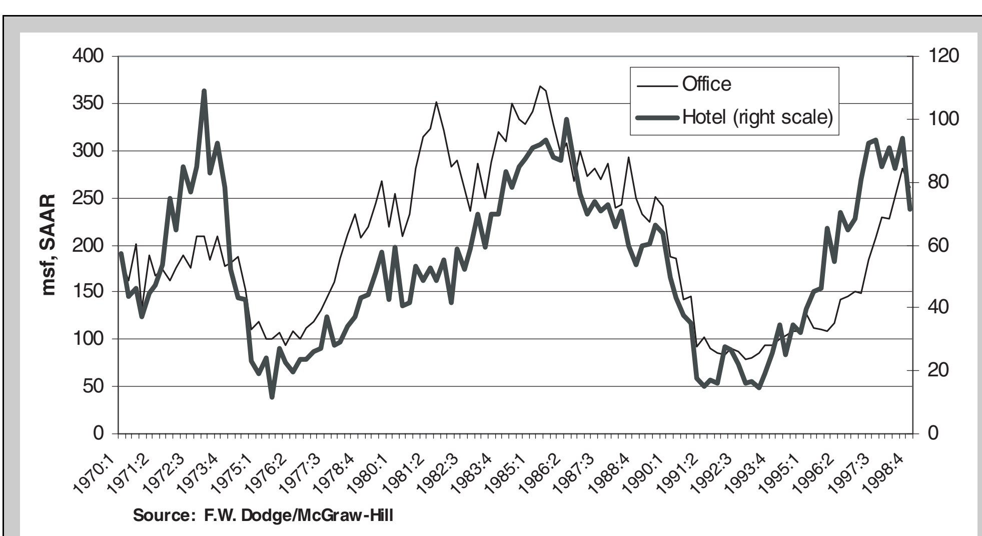


Exhibit 2 | Comparison of Property Market Supply Growth

	Annual Percentage Change in Stock (1970–1998) (%)	Sum of Completions as Share of Stock (1994–1998) (%)
Office	2.1	5.6
Retail	1.8	11.3
Warehouse	3.7	10.6
Hotel	4.8	11.2

Source: F. W. Dodge / McGraw-Hill.

commercial property sectors, the hotel market shows the highest long-term growth as reflected in the 4.8% annual percentage change in stock. Hotels have shorter functional lives than other property sectors, with styles and hotel formats changing constantly. To remain competitive and attract a more global clientele, the hotel industry has been constantly reinventing itself, leading to higher levels of construction activity. This is very similar to what has been happening in the retail industry, with the steady emergence of different retail formats. During the last few years, in particular, the hotel industry has experienced phenomenal new construction. Since 1994, construction of hotel and retail space has been much stronger than that for office or industrial space. The large hotel building boom has been partly a result of increased product segmentation, with most of the new construction comprised of the limited service and business traveler extended stay varieties (see Exhibit 3). The desire to establish global brand names that appeal to travelers has also led to a merger and acquisitions frenzy in the lodging industry in the United States. This, coupled with record-breaking profits since the 1991 recession, has provided further stimuli to new construction.

In comparison to the office market in general and to hotel supply, performance of hotel demand is more closely associated with the overall health of the economy. The hotel market has usually been the first hit in view of a negative economic shock, suffering immediately. Demand for hotel rooms is much more sensitive to ''event risk'' for a variety of factors. One of the most distinguishing features of the hotel market that separates it from the office market is its lease structure. Unlike office, retail and industrial space that rely on long-term leases, hotels rely on daily check-ins and daily check-outs, which are highly sensitive to underlying economic conditions. If a room is not used, the hotel loses immediately. Indeed, guest rooms are the most perishable income you have. If you do not use it today, it's gone.

By contrast, office rental contracts are usually long-term (anywhere from three to fifteen years) versus hotels which, effectively, have daily leases. The longer lease term effectively transfers a greater degree of ownership of the property to the

Exhibit 3 | Hotel Construction by Product Type (%)
(Hotel Starts in the Top 110 Metro Areas)

	1997 (%)	1998 (%)
Casino / Theme Park	16.3	2.4
Economy	22.3	17.3
Midprice w / o Food & Beverage	18.4	23.2
Midprice with Food & Beverage	6.0	4.3
Mixed Use	5.4	4.2
Other Hotel	8.8	16.1
Upscale	16.4	20.4
Upper Upscale	6.4	12.1

Source: F. W. Dodge / McGraw-Hill.

tenant. With very long-term leases, the landlord has effectively sold the rights to an uncertain market income stream in exchange for the present discounted value of all lease payments. A shorter lease term has a higher risk of vacancy but it allows the landlord to benefit from increases in market rental rates on a daily basis. As such, hotels are probably the most effective inflation-hedging investment since rents can be adjusted on a daily basis. Leases that have less optimal inflation adjustment clauses typically govern rents from other forms of real estate.

In the office market, owners incur significant transaction costs when space is occupied by new or different tenants, rendering a longer-term lease more desirable. According to Grenadier (1995), the presence of these costs makes landlords reluctant to drop rents as soon as unexpected vacant space develops. This has been one explanation for the persistence of high or low vacancy rates in the office market. In the hotel market, the transaction costs associated with new guests accounts for a smaller share of room rental rates, just the room cleaning expense and some paper work, and leases are renewed on a daily basis. Therefore, Grenadier's argument that large transaction costs prevent landlords from adjusting rents does not readily apply to the hotel market. Rents would be expected to adjust much quicker to unanticipated changes in occupancy rates and this should prevent periods of persistently high or low hotel occupancy rates (or vacancy rates) as observed for offices. Yet, hotel occupancy rates also appear to adjust slowly to underlying demand shocks.

In the case of hotels, the presence of price discrimination may be one mechanism that creates demand for some level of vacant space. Hotel operating companies price discriminate, charging different classes of consumers (say tourists versus business/corporate travelers) different rates, similar to the airline industry. The price-discriminating hotel operator will charge a higher price in that market in which demand is less responsive to price changes. Tactics such as advanced hotel reservations, Saturday-night stay-overs, minimum stay provisions, etc., are used to differentiate between business travelers (with relatively inelastic demands) and discretionary travelers (*i.e.*, tourists with more elastic demands). In addition, hotels often use peak-load price discriminating behavior. Typically, hotels located in vacation areas use peak-load pricing, charging higher prices during periods of increased demand. For example, hotel prices in Maine increase during the summer and decrease during the winter. Analogously, hotel rates at ski areas increase in the peak winter months in Colorado. It may, thus, be optimal for the hotel operator to maintain some level of vacancy for the higher-rate guests. Such profit-maximizing pricing behavior cannot persist, however, in markets where there is a lot of competition.

One implication of this analysis is that the higher-degree of volatility associated with hotel real estate is not only a function of supply but of demand. The supply cycles of hotel real estate appear to follow the general pattern of that observed for other categories of commercial real estate. By contrast, the nature of the daily leases creates much more volatility on the demand side.

Local Market Dynamics and REVPAR

Recent studies of hotel real estate have focused exclusively on the national market (see, for example, Wheaton and Rossoff, 1997). Since local markets exhibit widely different cycles and behavior, our primary focus is to examine metro level hotel dynamics. The metro level hotel construction cycles are much more volatile than that which would be implied by the aggregate construction cycle. This leads us to conclude that cyclicality is not only a function of property type but of geographic location as well. Exhibit 4 provides descriptive statistics characterizing demand and supply behavior across the various hotel markets. The top ten markets, as ranked by supply volatility, include the top tourist destinations such as Orlando, Orange County and Atlanta, and the smaller hotel markets such as Hartford, Birmingham and Greenville. The increased construction activity on the part of Disney and Universal Studios in Orlando and Orange County, and the 1996 Olympics in the case of Atlanta, have contributed to the supply volatility among the metro areas. Orlando also has the second-highest national hotel stock per capita (following Las Vegas). One implication for this is that the cyclical nature of the tourism industry has made the hotel markets that are prime tourist destinations more cyclical than average. The tourism industry itself is highly event sensitive and dependent on the underlying economic conditions.

The markets with the lowest degree of supply volatility include some of the larger hotel markets such as New York, Los Angeles, Boston, Chicago and Washington, DC. These are highly urbanized markets with higher degrees of population density that act as both tourist and business/convention destinations. They also account

Exhibit 4 | Metro Area Market Dynamics

Metropolitan Area	Supply Volatility	Rank	Hotel Stock Per Capita (rank)	Demand Volatility	Rank	Occupancy 1998
Tampa, FL	15.3	1	22	2.6	49	64.0
Birmingham, AL	15.2	2	40	5.1	9	59.6
Orange County, CA	14.2	3	15	4.6	13	65.1
Orlando, FL	13.7	4	2	5.4	7	75.3
Fort Worth, TX	12.9	5	44	5.6	5	61.9
Indianapolis, IN	11.9	6	24	3.2	32	61.9
Jacksonville, FL	10.7	7	12	2.8	42	62.5
Hartford, CT	10.5	8	55	3.2	34	67.7
Atlanta, GA	9.9	9	9	3.1	37	65.1
Greenville, SC	8.8	10	42	6.8	1	58.4
Charlotte, NC	8.3	11	16	3.3	31	63.4
Oakland, CA	8.2	12	57	4.3	16	73.1
Milwaukee, WI	8.1	13	56	3.9	21	63.9
Nashville, TN	7.9	14	8	2.7	46	63.1
Fairfield-New Haven, CT	7.3	15	53	3.1	38	65.5
Kansas City, MO	7.1	16	20	2.7	47	65.5
Honolulu, HI	7.0	17	3	3.6	23	72.6
Norfolk, VA	6.4	18	21	2.2	55	59.4
Denver, CO	6.3	19	26	3.2	36	69.7
Greensboro, NC	6.2	20	32	2.5	50	62.1
Columbus, OH	6.2	21	31	4.4	14	64.6

Exhibit 4 | (continued)

Metro Area Market Dynamics

Metropolitan Area	Supply Volatility	Rank	Hotel Stock Per Capita (rank)	Demand Volatility	Rank	Occupancy 1998
Austin, TX	6.2	22	18	2.3	53	67.6
New Orleans, LA	5.8	23	7	3.5	24	68.3
San Francisco, CA	5.8	24	4	2.7	45	77.8
Tulsa, OK	5.7	25	25	4.2	18	61.0
Oklahoma City, OK	5.7	26	36	2.7	44	55.7
Houston, TX	5.7	27	29	4.3	17	64.0
San Diego, CA	5.7	28	14	4.6	12	73.1
Philadelphia, PA	5.5	29	51	3.4	25	69.0
Detroit, MI	5.4	30	54	5.1	10	66.1
Raleigh, NC	5.2	31	17	2.0	57	65.1
Dallas, TX	5.0	32	11	2.7	48	66.2
Newark, NJ	4.8	33	47	4.0	20	75.4
Richmond, VA	4.7	34	30	3.0	41	61.9
Cleveland, OH	4.7	35	48	3.3	28	64.2
Seattle, WA	4.7	36	28	3.2	33	71.5
Riverside, CA	4.7	37	35	5.7	4	59.2
San Jose, CA	4.6	38	37	4.3	15	75.2
Phoenix, AZ	4.6	39	19	2.1	56	65.2
Nassau, NY	4.4	40	58	4.9	11	74.7
Las Vegas, NV	4.4	41	1	5.2	8	78.4

Exhibit 4 | (continued)

Metro Area Market Dynamics

Metropolitan Area	Supply Volatility	Rank	Hotel Stock Per Capita (rank)	Demand Volatility	Rank	Occupancy 1998
Minneapolis, MN	4.4	42	34	3.0	40	68.5
Salt Lake, UT	4.3	43	27	3.0	39	64.5
San Antonio, TX	4.1	44	23	6.4	2	64.8
Baltimore, MD	4.0	45	52	3.4	27	68.9
Pittsburgh, PA	3.9	46	49	3.4	26	63.5
Sacramento, CA	3.8	47	39	4.1	19	62.0
Portland, OR	3.5	48	45	3.7	22	62.2
Washington, DC	3.5	49	13	2.5	52	72.1
Chicago, IL	3.4	50	43	2.2	54	71.2
Cincinnati, OH	3.4	51	33	2.8	43	58.9
W. Palm, FL	3.2	52	6	2.5	51	68.5
Boston, MA	3.0	53	46	3.3	30	72.8
Los Angeles, CA	3.0	54	41	3.2	35	69.6
Fort Lauderdale, FL	3.0	55	10	5.4	6	68.4
St. Louis, MO	2.9	56	38	1.9	58	62.5
Miami, FL	2.4	57	5	5.8	3	70.6
New York, NY	2.1	58	50	3.3	29	81.3

Notes: Supply volatility is the standard deviation of annual completions as a % of stock, 1970–98. Demand volatility is the standard deviation of annual absorption as a % of Occ. Stock, 1988–98.
Source: F. W. Dodge and Smith Travel Research.

for the top revenue-generating markets, representing some of the most important profit drivers of the hotel industry.

Metro areas that enjoy the highest occupancy rates include the nation's most popular tourist destinations as well as the national convention and business travel hubs. This includes New York, Las Vegas, Orlando and San Francisco. Newark's high occupancy rate reflects its prime role as a major airport market relative to its size as measured by population.

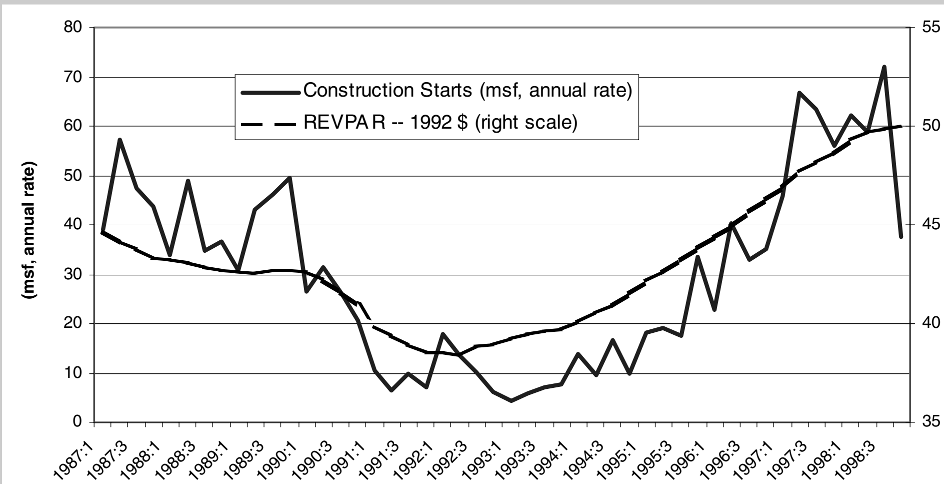
Measures of hotel financial performance provide further insight into local hotel market dynamics. With the increasing popularity of hotels as a real estate investment class through the expansion of REITS and commercial mortgage-backed securities, investors have sought measures of property returns and financial performance. Until recently, there was no benchmark measure of hotel property returns such as the NCREIF indices for commercial and apartment sectors.[3] Over the past several years, however, hotel revenue per available room (REVPAR) has become a popular concept for analyzing hotel financial performance. The concept has particular appeal to analysts, since it combines changes in occupancy and average daily rates (ADR). It is calculated by first multiplying the average daily rate by the number of occupied room nights for a given period to determine total room revenue. This figure is then divided by the total inventory of available room nights for the given period:

$$REVPAR_t = (ADR_t^{*}\ Occupied\ Rooms_t)/Room\ Inventory_t. \qquad (1)$$

REVPAR captures the interaction of ADR and occupancy at different phases of the hotel real estate cycle. In the short-run, REVPAR changes in response to movements in demand. In many instances, hotel operators may only increase short-term average daily rates at the expense of reduced occupancy. In the longer-run, REVPAR changes in response to net hotel additions to supply. Thus, REVPAR simultaneously reveals both the supply and demand dynamics of a hotel market cycle in one index.[4] Exhibit 5 graphs REVPAR and hotel construction starts for the nation's top fifty-eight markets for the last ten years.[5] It reveals the importance of REVPAR as a driver of new hotel development.

Exhibit 6 shows rankings for fifty-eight of the largest metropolitan areas based on changes in hotel REVPAR growth in 1998. The top performing markets were concentrated on the East and West Coast, including San Diego, New York City, Newark and Los Angeles. These markets are premier vacation and convention destinations as well as major airport hubs. Salt Lake City, among the worst performing markets, is reeling from high levels of completions, while occupancy rates in Honolulu have been hurt as a result of decreased tourism from Asia. Exhibit 6 also presents 1998 hotel starts as a percentage of existing inventory, a measure of future excess supply risk and possibility of weakening financial performance. In 1998, Fort Lauderdale, Fort Worth and Dallas were the most

Exhibit 5 | REVPAR and Hotel Starts Have Increased Substantially This Decade
(Average of Fifty-Eight Markets)



Source: F.W. Dodge and Smith Travel Research

active hotel construction markets in terms of their existing inventory. Fort Lauderdale is becoming an increasingly important vacation market, and the Dallas-Fort Worth area is capitalizing on its role as a prime national and regional distribution hub.

Hotel REVPAR may also be used to understand and compare hotel markets in terms of revenue volatility and relative growth. Investors may also use the concept to develop buy/sell strategies based on market cycle trends and to assess portfolio diversification. Several studies in the real estate literature have extended the concept of portfolio diversification in real estate beyond the straightforward mean-variance approach found in financial theory. Studies such as those by Miles and McCue (1984), Hartzell, Hekman and Miles (1986) and Hartzell, Shulman and Wurtzebach (1987) have demonstrated real estate diversification strategies based on geographic or industry dimensions.

As a basis for diversification analysis, REVPAR covariance measures at the metropolitan level can illustrate similarities in real estate cycles between markets and highlight the important trends in local hotel market dynamics. As part of an active portfolio management strategy, investors may use this analysis to reduce overall portfolio risk by investing in hotel markets that tend to be negatively or weakly correlated with the markets that comprise existing holdings.

Exhibit 7 provides a summary of correlation analysis for the fifty-eight metropolitan areas based on annual percentage changes in REVPAR from 1988

Exhibit 6 | Top Ranking REVPAR Growth Markets

Metropolitan Area	REVPAR % Change 1997–1998	REVPAR % Change 1996–1997	Starts as a % of Existing Stock 1998	Rank
San Diego, CA	15.9	14.6	3.7	41
Nassau, NY	13.2	10.6	3.0	45
Newark, NJ	12.2	13.9	0.0	58
New York, NY	9.9	12.7	2.5	49
Los Angeles, CA	9.2	10.4	1.2	54
Tulsa, OK	8.7	2.9	2.2	52
Hartford, CT	8.6	8.7	2.4	51
Riverside, CA	8.4	8.7	1.1	55
San Jose, CA	7.7	18.5	8.1	11
Oakland, CA	7.6	16.9	9.7	7
Chicago, IL	7.2	9.0	6.0	25
Norfolk, VA	7.0	5.5	3.0	46
Boston, MA	6.9	12.6	6.1	23
San Francisco, CA	6.8	14.3	3.5	43
Baltimore, MD	6.8	8.6	11.5	6
Washington, DC	6.7	10.1	4.7	35
Fairfield-New Haven, CT	6.7	9.7	4.1	39
Sacramento, CA	6.1	11.0	6.7	20
San Antonio, TX	5.9	0.7	7.6	15
Greensboro, NC	5.3	2.5	7.3	17
Detroit, MI	5.3	5.2	1.5	53
Houston, TX	5.0	10.5	5.5	30
Philadelphia, PA	4.8	10.5	3.8	40
Seattle, WA	4.7	6.8	7.5	16
Miami, FL	4.6	8.8	5.8	28
Milwaukee, WI	4.6	4.9	5.0	33
Atlanta, GA	4.2	−10.5	5.6	29
W. Palm, FL	3.9	14.4	4.2	38
Dallas, TX	3.9	1.4	12.4	3
Charlotte, NC	3.9	5.7	12.3	4
Minneapolis, MN	3.7	4.0	4.5	37
Tampa, FL	3.6	10.7	5.9	27
Fort Worth, TX	3.4	2.7	12.8	2
Columbus, OH	2.6	7.2	8.3	10

Exhibit 6 | (continued)

Top Ranking REVPAR Growth Markets

Metropolitan Area	REVPAR % Change 1997–1998	REVPAR % Change 1996–1997	Starts as a % of Existing Stock 1998	Rank
New Orleans, LA	2.6	3.3	3.4	44
Richmond, VA	2.3	6.6	4.7	34
Birmingham, AL	2.3	−4.3	2.9	47
Austin, TX	1.8	2.0	7.9	12
Denver, CO	1.6	7.7	5.1	32
Orange County, CA	1.5	7.3	3.7	42
Fort Lauderdale, FL	0.7	11.3	13.6	1
Cincinnati, OH	0.7	2.2	5.1	31
St. Louis, MO	0.7	1.2	1.0	56
Orlando, FL	0.7	9.1	7.8	13
Cleveland, OH	0.7	6.3	6.8	19
Pittsburgh, PA	0.2	−0.4	2.7	48
Indianapolis, IN	−0.3	2.8	2.4	50
Oklahoma City, OK	−0.6	0.9	8.6	9
Las Vegas, NV	−1.0	−0.2	6.0	26
Jacksonville, FL	−1.1	4.7	7.0	18
Kansas City, MO	−1.9	5.4	4.5	36
Greenville, SC	−2.5	−5.3	6.1	24
Portland, OR	−3.1	−1.4	9.7	8
Nashville, TN	−3.5	5.9	6.6	21
Phoenix, AZ	−5.0	2.3	11.6	5
Honolulu, HI	−6.7	1.4	0.0	57
Raleigh, NC	−7.6	1.9	7.8	14
Salt Lake, UT	−8.9	−0.3	6.6	22

Source: F. W. Dodge and Smith Travel Research.

to 1998. The first and second columns show the correlation coefficient of the individual metropolitan area's REVPAR growth to the fifty-eight market average, while the third, fourth, fifth and sixth columns show its corresponding most- and least-correlated markets. REVPAR growth for a large number of metro areas is highly correlated with the overall market average. Thirty of the fifty-eight markets registered correlation coefficients in excess of 0.5, with Baltimore, Charlotte, Richmond, Philadelphia and New York ranking the highest. A majority of these

Exhibit 7 | REVPAR Correlation Rankings

Metropolitan Area	Correlation with Market Average	Most Correlated With:	Correlation	Least Correlated With:	Correlation
Baltimore, MD	0.95	Nassau, NY	0.97	San Antonio, TX	−0.46
Charlotte, NC	0.95	Richmond, VA	0.92	San Antonio, TX	−0.48
Richmond, VA	0.94	Philadelphia, PA	0.95	San Antonio, TX	−0.46
Philadelphia, PA	0.92	Richmond, VA	0.95	San Antonio, TX	−0.61
New York, NY	0.92	San Jose, CA	0.94	San Antonio, TX	−0.38
Fairfield-New Haven, CT	0.91	Chicago, IL	0.97	Austin, TX	−0.37
Nassau, NY	0.90	Baltimore, MD	0.97	Houston, TX	−0.37
Chicago, IL	0.90	Fairfield-New Haven, CT	0.97	San Antonio, TX	−0.45
Detroit, MI	0.88	Charlotte, NC	0.90	Houston, TX	−0.49
San Jose, CA	0.88	New York, NY	0.94	San Antonio, TX	−0.43
Hartford, CT	0.88	New York, NY	0.93	San Antonio, TX	−0.52
Boston, MA	0.88	Fairfield-New Haven, CT	0.96	Austin, TX	−0.34
Jacksonville, FL	0.87	Charlotte, NC	0.85	Houston, TX	−0.38
San Francisco, CA	0.87	Philadelphia, PA	0.95	San Antonio, TX	−0.57
Orange County, CA	0.82	San Jose, CA	0.90	San Antonio, TX	−0.38
Norfolk, VA	0.81	Nassau, NY	0.96	Salt Lake, UT	−0.40
Los Angeles, CA	0.80	New York, NY	0.93	Austin, TX	−0.42
Oakland, CA	0.79	San Jose, CA	0.90	San Antonio, TX	−0.52
Milwaukee, WI	0.79	Greensboro, NC	0.84	Salt Lake, UT	−0.18
Newark, NJ	0.77	Chicago, IL	0.95	San Antonio, TX	−0.36
Kansas City, MO	0.76	Raleigh, NC	0.85	Houston, TX	−0.48

Exhibit 7 | (continued)
REVPAR Correlation Rankings

Metropolitan Area	Correlation with Market Average	Most Correlated With:	Correlation	Least Correlated With:	Correlation
San Diego, CA	0.72	Baltimore, MD	0.86	San Antonio, TX	−0.45
Cincinnati, OH	0.72	Boston, MA	0.81	San Antonio, TX	−0.42
Tampa, FL	0.71	San Jose, CA	0.92	Austin, TX	−0.40
Riverside, CA	0.71	Tampa, FL	0.91	Austin, TX	−0.43
Washington, DC	0.70	W. Palm, FL	0.86	New Orleans, LA	−0.33
Cleveland, OH	0.70	Greenville, SC	0.79	Houston, TX	−0.37
W. Palm, FL	0.70	Washington, DC	0.86	Houston, TX	−0.43
Columbus, OH	0.68	Fort Lauderdale, FL	0.87	Tulsa, OK	−0.32
Nashville, TN	0.68	Phoenix, AZ	0.88	Houston, TX	−0.56
Seattle, WA	0.68	San Jose, CA	0.85	San Antonio, TX	−0.39
St. Louis, MO	0.66	Phoenix, AZ	0.90	Houston, TX	−0.56
Dallas, TX	0.66	Jacksonville, FL	0.77	Houston, TX	−0.39
Phoenix, AZ	0.63	St. Louis, MO	0.90	Houston, TX	−0.49
Indianapolis, IN	0.62	Phoenix, AZ	0.83	San Antonio, TX	−0.54
Las Vegas, NV	0.62	Phoenix, AZ	0.78	Houston, TX	−0.33
Raleigh, NC	0.60	Phoenix, AZ	0.88	Houston, TX	−0.61
Orlando, FL	0.55	Tampa, FL	0.86	Austin, TX	−0.39
Greensboro, NC	0.55	Milwaukee, WI	0.84	Houston, TX	−0.53
Greenville, SC	0.53	Cleveland, OH	0.79	Houston, TX	−0.51

Exhibit 7 | (continued)

REVPAR Correlation Rankings

Metropolitan Area	Correlation with Market Average	Most Correlated With:	Correlation	Least Correlated With:	Correlation
Sacramento, CA	0.47	W. Palm, FL	0.85	Houston, TX	−0.44
Pittsburgh, PA	0.47	Dallas, TX	0.72	Houston, TX	−0.26
Fort Lauderdale, FL	0.46	Columbus, OH	0.87	Birmingham, AL	−0.52
Atlanta, GA	0.37	St. Louis, MO	0.75	Houston, TX	−0.67
Fort Worth, TX	0.36	Birmingham, AL	0.81	San Antonio, TX	−0.62
Minneapolis, MN	0.31	Sacramento, CA	0.73	Houston, TX	−0.77
Denver, CO	0.29	Raleigh, NC	0.67	San Antonio, TX	−0.61
Miami, FL	0.24	Fort Lauderdale, FL	0.87	St. Louis, MO	−0.38
Oklahoma City, OK	0.21	Cleveland, OH	0.71	Denver, CO	−0.36
Honolulu, HI	0.19	Orlando, FL	0.64	Denver, CO	−0.38
Portland, OR	0.19	Salt Lake, UT	0.72	Sacramento, CA	−0.43
Birmingham, AL	0.13	Fort Worth, TX	0.81	Fort Lauderdale, FL	−0.52
Salt Lake, UT	0.12	Portland, OR	0.72	San Diego, CA	−0.42
Tulsa, OK	0.02	Riverside, CA	0.52	Minneapolis, MN	−0.50
New Orleans, LA	0.00	Honolulu, HI	0.47	Denver, CO	−0.34
Austin, TX	−0.08	Indianapolis, IN	0.65	Houston, TX	−0.43
Houston, TX	−0.19	Tampa, FL	0.33	Minneapolis, MN	−0.77
San Antonio, TX	−0.44	New Orleans, LA	0.16	Fort Worth, TX	−0.62

metro areas are located in the more-mature urbanized centers along the East Coast. Only three metropolitan areas located in Texas, Austin, Houston and San Antonio, were negatively correlated with the market average. Such negative correlations are not surprising, however, given the unique boom and bust cycle experienced by the Texas metro areas in the 1980s. The fifth and sixth columns of Exhibit 7 also show that San Antonio, Austin and Houston are consistently the least correlated with other metropolitan areas.

Cluster Analysis of Hotel REVPAR Performance

An alternate approach that may be used to highlight differences in hotel market performance and structure involves the identification of statistically similar groupings, or clusters of metropolitan areas, based on their historical REVPAR performance. Such clusters could provide investors with improved guidelines for allocating hotel investments across geographic areas in order to help minimize overall portfolio risk. The advantage of a statistical clustering approach stems from the ability to group markets on the basis of maximizing each group's within-group homogeneity while also maximizing differences between groups. Goetzmann and Wachter (1995) formalize a clustering approach for identifying groups of metropolitan area office markets on the basis of rental growth and vacancy. More recently, Cheng and Black (1998) apply clustering methods to find similar apartment markets, and then use multiple discriminant analysis to identify economic variables that explain market segmentation.

While statistical clustering analysis can be a useful approach for identifying groups of like markets, it entails a degree of subjectivity. The decision rules for determining the number of clusters that are ultimately included in the analysis can often be subject to varied interpretations. Cluster assignments are highly dependent on the selected statistical algorithm. Furthermore, the stability of cluster assignments may vary significantly across time periods and markets included in the analysis.

Our analysis of hotel market dynamics includes a statistical clustering approach based on 1988–1998 annual percentage changes in inflation-adjusted REVPAR for fifty-eight markets. A hierarchical clustering procedure, based on a variant of the Howard-Harris algorithm, was executed. Five distinct clusters were identified through the procedure and are shown in Exhibit 8. Additional clusters were not found to produce a significant reduction in total within-cluster variance.

To a degree, several clusters share some common geographic and metropolitan area economic structures that may be generalized intuitively. Cluster 1 consists of large (and more mature, slower growing) business centers that are geographically concentrated along the East and West coasts. Cluster 2 contains a number of smaller, emerging economies. Several of the metro areas in this cluster are dependent on port and international trade activity. Cluster 3 includes a number of markets that have a significant resource-industry component, geographically centered in New Orleans, and several Texas and Oklahoma cities. Cluster 4

Exhibit 8 | Cluster Groupings

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Boston, MA	Greensboro, NC	Cleveland, OH	Baltimore, MD	Atlanta, GA
Charlotte, NC	Indianapolis, IN	Houston, TX	Columbus, OH	Austin, TX
Chicago, IL	Kansas City, MO	New Orleans, LA	Fort Lauderdale, FL	Birmingham, AL
Cincinnati, OH	Miami, FL	Oklahoma City, OK	Honolulu, HI	Dallas, TX
Detroit, MI	Norfolk, VA	Portland, OR	Jacksonville, FL	Denver, CO
Greenville, SC	Oakland, CA	Salt Lake, UT	Las Vegas, NV	Fort Worth, TX
Hartford, CT	Sacramento, CA	San Antonio, TX	New York, NY	Minneapolis, MN
Los Angeles, CA	St. Louis, MO	Tampa, FL	Orange County, CA	Nashville, TN
Milwaukee, WI	Washington, DC	Tulsa, OK	Orlando, FL	Phoenix, AZ
Nassau, NY			Pittsburgh, PA	Raleigh, NC
Fairfield-New Haven, CT			Riverside, CA	San Diego, CA
Newark, NJ			San Jose, CA	
Philadelphia, PA			Seattle, WA	
Richmond, VA			W. Palm, FL	
San Francisco, CA				

includes several top tourist destinations such as New York City, Las Vegas, Orlando, West Palm, Fort Lauderdale and Honolulu. Cluster 5, on the other hand, is comprised of several fast-growing emerging business centers, such as Atlanta, Austin, Dallas, Raleigh, Phoenix and San Diego. These are also among the nation's most important emerging high-tech and information technology centers.[6]

Exhibit 9 shows the annual percentage change in inflation-adjusted REVPAR for each of the cluster means over the past eleven years. Each cluster shows a distinct pattern. Cluster 1 has tended to perform poorly in terms of REVPAR growth through much of the 1990s, posting a modest increase in 1998. This mirrors national REVPAR performance over this period. In contrast, inflation-adjusted REVPAR for Clusters 3 and 5 grew consistently throughout the entire sample period, insulated from the national recession during the early part of the decade. Clusters 2 and 3 also experienced fairly strong REVPAR growth over this period, with a few exceptions. Cluster 2's mean REVPAR stagnated in 1992, while Cluster 4's performance weakened considerably in 1997 and 1998. Cluster 4 includes the nation's top tourist destinations, which were disproportionately hurt by a global fall-off in demand resulting from the Asian and Latin American financial crises.

Exhibit 9 | Cluster Means—Inflation-adjusted REVPAR % Change: 1988–1998

	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998
CLUSTER 1	1.7	1.7	1.8	−0.4	−0.2	−0.2	−0.5	0.1	−0.2	−0.7	1.3
CLUSTER 2	1.3	0.6	1.2	2.2	−1.0	2.9	1.7	0.5	1.0	1.3	0.6
CLUSTER 3	1.8	3.4	2.9	2.1	1.6	2.0	2.4	1.7	2.6	1.8	3.4
CLUSTER 4	1.4	1.1	1.4	0.1	1.4	2.4	2.8	0.3	1.4	0.0	−0.7
CLUSTER 5	1.1	4.6	1.2	2.6	3.9	2.6	2.1	1.0	2.1	1.9	1.6

REVPAR Performance, Economic Characteristics and Multiple Discriminant Analysis

The relationship between cluster assignments and the underlying metropolitan area economic charateristics may be formalized statistically. In particular, through multiple discriminant analysis (MDA), a linear model may be constructed to explain to what degree the cluster membership is related to cross-sectional market demand and economic characteristics. This resembles the methodology set forth by Cheng and Black (1998) for the apartment market.

Sharma (1992) notes that MDA has three primary purposes. First, MDA may be used to identify the variables that discriminate "best" between the groups. Second, the identified variables may be used to develop a set of functions (the discriminant functions) for computing an index that will efficiently represent the differences between multiple groups. Finally, the variables and computed index may be used to classify future observations into one of the groups.

The basic mechanics of discriminant analysis are as follows. First, each metropolitan statistical area is assigned a numerical code (from 1 to 5) to identify its cluster membership. Then, a statistical F-test is performed that can determine which variables have the most significantly different cluster means. Those variables with the most significant differences are included as candidates for the set of identifying or "discriminating" variables. After identifying these variables, the next step is to estimate an appropriate set of discriminant functions. Mathematically, the discriminant function may be represented by the following:

$$Z_i = w_{i1}X_1 + w_{i2}X_2 + \ldots + w_{ip}X_p, \tag{2}$$

where Z_i represents the discriminant scores for each discriminant function i, X_p represents p economic (or discriminating variables) and w_i represents the variable weights in the discriminant function. Up to four unique functions may be determined (one less than the total number of groups) to distinguish among the groups. Finding the appropriate weights and number of discriminant functions is the optimization problem. For the first discriminant function, weights are calculated by maximizing the between-groups sum of squares of the underlying variable relative to within-groups sum of squares. This procedure is repeated for additional functions with the provision that the underlying discriminant scores are uncorrelated.[7]

A multiple discriminant analysis was performed with the five metropolitan area cluster assignments as the grouping variable. Exhibit 10 lists the metropolitan area demand and economic characteristics that were selected for the analysis. The variables were selected to determine whether economic growth, structure, or hotel supply and demand factors differentiated cluster assignments. Since metropolitan

Exhibit 10 | Variables Used in Discriminant Analysis

Variable	Description
HOTKNR	Hotel stock per capita
HOTKGR	Hotel stock per capita % growth, 1987–1998
YPNR92C	Real per capita income, chained 1992$
LQEDEMP	Location quotient, eating and drinking place employment
LQAREMP	Location quotient, amusement and recreation service employment
EOFFGR	Office employment growth, avg. 1987–1998
INTLK	International visitors per unit of hotel stock
	Employment Location Quotient: 1998
LQEMI	Mining
LQEFIR	FIRE industries
LQET	Trade
LQESV	Services
LQEM	Manufacturing
LQEG	Government
	Employment growth: avg. 1987–1998
EMIGR	Mining
EFIRGR	FIRE employment
ETGR	Trade
ESVGR	Services
EMGR	Manufacturing
EGGR	Government

area economic time series are often limited to broad employment and income measures, several employment categories were included to determine if the variables could distinguish between the apparent business and tourism-related dimensions of the metropolitan area clusters. These variables included average growth by the major industrial (one-digit SIC code) and office-related employment sectors over the 1987–1998 period. In addition, the analysis included 1998 employment location quotients by major sector, including high-tech, amusement and recreation services, and eating and drinking place employment. Furthermore, a measure of industry concentration, based on a variant of the Hershmann-Herfindahl Index, was added to determine whether REVPAR performance tended to group by markets characterized by few dominant industries. The remaining demand side variables included the proportion of international visitors per unit of hotel space and real per capita income. On the supply side, hotel stock per capita and its average growth rate over the 1987–1998 period were included.[8]

Exhibit 11 shows the Wilks' Lambda and corresponding *F*-test for equality of the discriminating variables' group means. Several variables have significantly different group means at the 1% level. These include office, government, manufacturing, services and trade employment growth. It is not surprising that many employment sectors are statistically significant, since employment growth tends to be somewhat uniform among sectors over extended time periods. In other words, the fastest-growing metropolitan areas tend to exhibit fast growth among each of their component sectors. Several location quotients are also significant at the 1% level. These include the location quotients for mining, eating and drinking places, and amusement and recreation services employment. The mining employment location quotient is associated with Cluster 3, which includes a number of resource-dependent markets such as Houston, New Orleans, Oklahoma City, Tulsa and Salt Lake City. The group means for this variable are shown in Exhibit 12. In addition, the location quotients for amusement and recreation services and eating and drinking places appear to distinguish the tourism-oriented

Exhibit 11 | Discriminant Analysis: Tests of Equality of Group Means

	Wilks' Lambda	*F*	*df*1	*df*2	Sig.
EFIRGR	0.877	1.855	4	53	0.132
EGGR	0.774	3.862	4	53	0.008
EMGR	0.772	3.916	4	53	0.007
EMIGR	0.955	0.626	4	53	0.646
EOFFGR	0.702	5.617	4	53	0.001
ESVGR	0.717	5.233	4	53	0.001
ETGR	0.704	5.578	4	53	0.001
HOTKNR	0.860	2.157	4	53	0.087
INTLK	0.912	1.276	4	53	0.291
IOCONC	0.899	1.493	4	53	0.217
LQAREMP	0.772	3.916	4	53	0.007
LQEDEMP	0.775	3.850	4	53	0.008
LQEFIR	0.940	0.848	4	53	0.501
LQEG	0.898	1.497	4	53	0.216
LQEM	0.854	2.256	4	53	0.075
LQEMI	0.624	7.980	4	53	0.000
LQESV	0.867	2.034	4	53	0.103
LQET	0.952	0.671	4	53	0.615
LQTECH	0.950	0.705	4	53	0.592
YPNR92C	0.800	3.320	4	53	0.017
HOTKGR	0.883	1.748	4	53	0.153

Exhibit 12 | Group Means

Variable	CLUSTER 1	CLUSTER 2	CLUSTER 3	CLUSTER 4	CLUSTER 5
EFIRGR	0.57	1.41	1.93	1.55	2.18
EGGR	0.68	1.00	1.81	1.83	2.27
EMGR	−1.42	−0.03	1.32	−0.37	0.89
EMIGR	−2.00	−2.65	−1.49	−2.69	−0.31
EOFFGR	0.97	1.72	2.43	2.39	2.70
ESVGR	3.09	3.91	4.75	4.33	5.26
ETGR	0.55	1.16	2.16	1.97	2.78
HOTKGR	2.56	2.41	1.91	2.71	3.48
HOTKNR	5.84	7.52	7.15	12.83	8.01
INTLK	0.03	0.03	0.02	0.04	0.02
IOCONC	456.25	540.93	506.09	555.07	515.95
LQAREMP	0.93	1.02	0.99	1.68	1.06
LQEDEMP	0.89	1.04	1.08	1.07	1.06
LQEFIR	1.25	1.06	1.07	1.19	1.12
LQEG	0.82	1.05	0.93	0.87	0.93
LQEM	1.06	0.81	0.79	0.70	0.85
LQEMI	0.14	0.18	2.42	0.19	0.69
LQESV	1.05	1.03	1.05	1.16	1.03
LQET	0.98	1.00	1.03	1.02	1.02
LQTECH	1.24	1.10	0.90	1.28	1.40
YPNR92C	27.86	24.20	22.19	26.07	24.37

markets grouped in Cluster 4. Average per capita income, which has different group means at the 5% level of significance, is associated with Cluster 1's above average per capita incomes.

From Exhibit 11, several variables appear to be likely candidates for constructing the discriminant functions. There is no indication, however, as to which variables are the statistically "best" set for analysis. Entering all of the likely variables into the estimation could prove to be problematic, since discriminant analysis is sensitive to multicollinearity. The presence of multicollinearity can lead to misclassification errors. To minimize such errors, a stepwise procedure was executed. Stepwise discriminant procedures have the advantage of selecting variables that have a high degree of between-groups explanatory power, while maintaining orthogonality of the selected discriminating variables.

The results of the stepwise procedure are found in Exhibit 13. Three variables entered into the discriminant function estimation: the location quotient for mining employment (*LQEMI*), average office employment growth (*EOFFGR*) and the location quotient for amusement and recreation services employment (*LQAREMP*). As Exhibit 14 shows, the selected variables have tolerance levels in excess of 0.8, indicating low levels of collinearity.

The results illustrate that the degree of business versus tourism market orientation plays a significant role in determining the cluster group assignments, and ultimately, financial performance. In addition, the significance of the mining location quotient demonstrates the uniqueness of the market characteristics that comprise Cluster 3. Exhibits 15–17 also show summary statistics for discriminant functions. There are several means of evaluating the significance or explanatory power of the functions. One method is the squared canonical correlation, which gives the proportion of the total sum of squares for the discriminant score that is due to the differences between the groups. For the three estimated discriminant functions, the squared canonical correlation ranges from 0.11 to 0.46, implying a moderate degree of explanatory power.

A classification matrix was also estimated to determine how well the discriminating variables group observations into appropriate clusters. Exhibit 18 shows the classification function coefficients. Exhibit 19 is the predicted group membership. Of the fifty-eight metropolitan areas in the analysis, 51.8% were correctly classified, with the success rates exceeding 60% for Clusters 1, 2 and 5. One method for evaluating the significance of the classification results involves making a comparison to a classification rate based on chance. The proportional chance criterion, a widely used comparison, is calculated by squaring and summing the proportions for each group. This calculated value for the hotel clusters is equal to 20.9%, below the classification rate based on the discriminant variables. Sharma (1992) notes that a normally distributed test statistic follows from the proportional chance criteria. In the equation below, n represents the total number of observations, n_g is the number of observations for each group g, e is the expected correct number of observations due to chance and o is the total number of correct classifications:

Exhibit 13 | Stepwise Discriminant Analysis

Variables Entered / Removed

						Exact *F*				Approximate *F*			
Step	Entered	Wilks' Lambda	*df*1	*df*2	*df*3	Statistic	*df*1	*df*2	Sig.	Statistic	*df*1	*df*2	Sig.
1	*LQEMI*	0.624	1	4	53	7.980	4	53	4.115E-05				
2	*EOFFGR*	0.443	2	4	53	6.532	8	104	7.037E-07				
3	*LQAREMP*	0.356	3	4	53					5.374	12	135.225	0.000

Note: At each step, the variable that minimizes the overall Wilks' Lambda is entered. the maximum number of steps is 42. The minimum partial *F* to enter is 2.85. The maximum partial *F* to remove is 1.65.

$$Z^* = (o - e)\sqrt{n}/\sqrt{e(n - e)}, \quad (3)$$

where:

$$e = 1/n \sum_{g=1}^{g} n_g^2.$$

The calculated statistic for the hotel clusters is 5.85, which is significant at the 1% level.

Although the discriminant function and the classification rates show a moderate amount of explanatory power, the results are influenced by a number of factors. First, several markets share business and tourism-oriented travel characteristics, which may obfuscate the linkage between cluster assignments and the office employment and amusement and recreation service variables. Second, additional statistical techniques may be applied, through K-means and bootstrapping methods, to refine the hierarchical cluster assignments. This may lead to higher

Exhibit 14 | Variables in the Analysis

Step		Tolerance	*F* to Remove	Wilks' Lambda
1	*LQEMI*	1.000	7.980	
2	*LQEMI*	0.997	7.610	0.702
	EOFFGR	0.997	5.316	0.624
3	*LQEMI*	0.997	6.870	0.548
	EOFFGR	0.831	4.654	0.486
	LQAREMP	0.832	3.097	0.443

Exhibit 15 | Summary of Canonical Discriminant Functions: Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	0.850	64.258	64.258	0.678
2	0.345	26.072	90.330	0.506
3	0.128	9.670	100.000	0.337

Note: The first three canonical discriminant functions were used in the analysis.

Exhibit 16 | Summary of Canonical Discriminant Functions: Wilks' Lambda

Test of Functions	Wilks' Lambda	Chi Square	*df*	Sig.
1–3	0.356	54.679	12	2.07E-07
2–3	0.659	22.079	6	0.001
3	0.887	6.378	2	0.041

Exhibit 17 | Summary of Canonical Discriminant Function Coefficients

	Function		
	1	2	3
EOFFGR	0.659	0.495	−0.724
LQAREMP	−0.333	0.649	0.818
LQEMI	0.816	−0.219	0.537

Exhibit 18 | Classification Results: Classification Function Coefficients

	CLUSTER 1	CLUSTER 2	CLUSTER 3	CLUSTER 4	CLUSTER 5
Constant	−2.997	−3.704	−7.435	−6.623	−5.496
EOFFGR	0.264	0.980	1.821	1.144	1.990
LQAREMP	2.679	2.407	1.836	4.313	1.782
LQEMI	0.197	0.262	2.230	0.323	0.737

Note: Fisher's linear discriminant functions.

levels of explanatory power and improved classification rates. In addition, the availability of discriminating variables is limited to broad demand and supply characteristics, which largely reflect employment changes. Ideally, the selection would include more information on travel characteristics and consumer and business spending patterns.

Exhibit 19 | Predicted Group Membership

		Predicted Group Membership					
	CLUSTER	1	2	3	4	5	Total
Original Count	1	9	5	0	0	1	15
	2	2	6	0	1	0	9
	3	1	0	4	0	4	9
	4	4	2	0	4	4	14
	5	0	2	0	2	7	11
%	1	60.0	33.3	0.0	0.0	6.7	100
	2	22.2	66.7	0.0	11.1	0.0	100
	3	11.1	0.0	44.4	0.0	44.4	100
	4	28.6	14.3	0.0	28.6	28.6	100
	5	0.0	18.2	0.0	18.2	63.6	100
Cross–Validated Count	1	9	5	0	0	1	15
	2	2	5	0	1	1	9
	3	1	0	4	0	4	9
	4	4	1	0	4	5	14
	5	0	2	1	2	6	11
%	1	60.0	33.3	0.0	0.0	6.7	100
	2	22.2	55.6	0.0	11.1	11.1	100
	3	11.1	0.0	44.4	0.0	44.4	100
	4	28.6	7.1	0.0	28.6	35.7	100
	5	0.0	18.2	9.1	18.2	54.5	100

Notes: Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case. 51.7% of original grouped cases correctly classified. 48.3% of cross-validated grouped cases correctly classified.

Conclusion

In this article, we initially provide a conceptual analysis of national and regional hotel market dynamics. On a national level, the hotel market cycle is compared to that for offices. The similarities between office and hotel construction cycles are quite remarkable. The construction lag between initiation and completion of the projects is an important element in both hotel and office construction cycles. Differences in hotel real estate and other commercial property markets are also highlighted. Among the most notable differences are hotel lease structures and the price-discrimination strategies of hotel operators. Hotel leases are effectively signed on a daily basis. This makes them a better inflation-hedge since rents can be adjusted daily. Relatively high vacancy rates can persist in hotel markets due to the price-discriminating behavior of hotel operators. There is an incentive to hold some vacant inventory of hotel rooms for the guests with less-elastic demands.

Since metro level hotel cycles appear more volatile than that for the nation, we focus on metropolitan level markets. Looking at various measures of supply and demand volatility, historical REVPAR growth, and various metro level REVPAR correlation statistics, distinctions are made across fifty-eight of the nation's largest hotel markets. It is found that the larger business travel and tourism markets exhibit higher degrees of both demand and supply volatility. REVPAR growth was also strongest for those hotel markets that are both major tourism centers, major business and convention centers, and major airport markets.

Next, cluster analysis is used to provide a more rigorous way of grouping the various metro hotel markets. We are successful in identifying five distinct clusters of hotel markets. A second major contribution of our study is to provide economic rationalizations behind the hotel groupings using discriminant analysis.

Cluster analysis provides a more rigorous method for revealing uncorrelated groups. This is a useful method in grouping like markets in order to improve geographic diversification decisions by hotel portfolio managers. By allocating capital across these uncorrelated groups, investment managers can significantly reduce the volatility of hotel real estate portfolio returns.

The use of cluster analysis can also help econometricians in building more robust models of real estate markets used for forecasting vacancy rates and property returns. Because of the short-time series nature of hotel demand variables, a pooling of cross-sectional time series methods is used to build econometric models. This requires the estimated parameters of the model to be identical across all metro areas. Pooling of cross-sectional variables across clusters can help refine forecasts and reduce errors.

A logical extension of this research is to test the insularity of each of the five hotel clusters in view of demand or supply shocks. Markets that exhibit a fair degree of insularity in view of negative shocks are ones that can optimize portfolio returns during periods of economic uncertainty.

Endnotes

[1] The correlation between the two series for the whole period was 83%, implying a 64% R^2.

[2] Occupancy follows the slower movements in supply.

[3] The American Hotel and Motel Association, in conjunction with the Cornell University School of Hotel Administration began publishing the Lodging Property Index (LPI) in the fourth quarter of 1995. The index reported income, capital and total return for a sample of 249 lodging properties. The inaugural index also reported geographic subsamples for the East, Midwest, South and West regions, as well as subsamples for upscale, midprice and economy market segments. See Corgel and deRoos (1997) for a detail discussion of index construction and methodology.

[4] For a detailed discussion of the REVPAR concept and its use in hotel market analysis, see Wolverton (1997).

[5] The REVPAR data is reported by F. W. Dodge/McGraw-Hill companies and is derived from quarterly occupancy and average daily room rate statistics from Smith Travel Research. The data presented in this analysis extends from 1987 through 1998.

[6] Note that this analysis does not include any evaluation of cluster stability. Alternative clustering algorithms may assign metropolitan areas to different clusters.

[7] Following Sharma (1992), since discriminant analysis involves inverting within-group matrices, the accuracy of the computations is affected if the matrices are near singular. In other words, if some of the discriminator variables are highly correlated, or are linear combinations of other variables, the estimates may be inaccurate. In order to compensate for this effect, the analyst may change the tolerance level, or the degree of multicollinearity that one is willing to accept. The tolerance level is equal to $1 - R^2$, where R^2 is the squared multiple correlation between the variable in question and other variables in the discriminant function.

[8] The employment and per capita income data source is Standard and Poor's/DRI. Hotel stock data are provided by the F. W. Dodge/McGraw-Hill companies. The international tourist arrivals are from Tourism Industries, International Trade Administration, U. S. Department of Commerce. Mathematically, the location quotient (LQ_i) for a particular industry ($_i$) in a local economy is determined as:

$$LQ_i = (E_i/E)/(E_{i,us}/E_{us}),$$

where E and E_{us}, are total employment at the local and national levels. The concentration ratio, a variant of the Hershmann-Herfindahl Index, is calculated by the following taking the sum of squared industry shares of total employment by MSA:

$$CONC = \sum(E_i/E)^2.$$

In addition, the detailed employment series on amusement, recreation services, and eating and drinking places are from Standard & Poor's/DRI Business Demographics database. DRI defines high-tech employment as the sum of employment in thirty-three industries at roughly the three digit Standard Industrial Classification (SIC) level.

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