Seasonality in Commercial Real Estate Transaction Volume and Capital Returns

by

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ABSTRACT

In this thesis I examine the existence of seasonality in quarterly transaction volume and capital returns in commercial real estate markets from 1984 to 2005, based on MIT's Transaction-Based Index. Evidence is provided that (1) transaction volume distributions in fourth quarter and capital returns distributions on all properties in third quarter have large means relative to the remaining three quarters; (2) there exists 4-quarter lagged systematic seasonality in capital returns on all properties, based on the results from an autocorrelation function.

Thesis Supervisor: Henry Pollakowski
Title: Principle Research Associate

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Finally, this thesis is dedicated to my wife, Yanjun Li, my parents and my baby. Their sacrifices and unwavering support throughout this disruptive year have made my educational experiences at MIT possible.

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Chapter 1 – Introduction

1.1 Background

In business world, seasonality is defined by changes in business, employment or buying patterns which occur predictably at given times of the year[1]. Generally, the existence of seasonality is due to some human seasonal purchase patterns, for example, retailers achieve much higher sales revenue in the period from Thanksgiving to Christmas than in any other periods in the year. There is abundant empirical evidence indicating that seasonality exists in almost every business industry. Through studying seasonality, people can develop appropriate business strategies to capture the market opportunities and test efficiency in specific markets.

1.2 Objectives and findings

There is little research about the seasonality in commercial real estate having been conducted, compared with the number of papers presenting the existence of seasonality in housing markets and capital markets. Motivated by the importance of seasonality and the lack of research on commercial real estate markets, this paper attempts to explore the existence of seasonality in transaction volume and capital returns in commercial real estate markets. The study examines the quarterly data in

[1] Based on www.mastercardbusiness.com/mcbizdocs/smallbiz/finguide/glossary.html

MIT’s Transaction-Based Index (TBI) during the period from first quarter of 1984 to fourth quarter of 2005.

The major conclusion drawn is that there are statistically significant differences in means by quarter of year due primarily to consistently large transaction volume in fourth quarter and capital returns in third quarter. Descriptive statistic as well as non-parametric tests provides the evidence that there are statistically significant differences in means by quarter of year due primarily to consistently large transaction volume in fourth quarter and capital returns in third quarter.

The rest of this paper is structured as follows. After a review of literature in section 2 and discuss about data in section 3, section 4 develops the methodology and presents evidence on the existence of seasonality. A final conclusion and future research are discussed in section 5, in which I explore the possible explanations for the observed seasonality. However, hypotheses which seek to explain seasonality are not tested in this paper, which I believe deserve elaboration in future research.

Chapter 2 – Literature Review

Although there is little previous research on seasonality in commercial real estate markets, extensive studies on seasonality in capital markets and housing markets could provide an appropriate and illustrative methodology for studying seasonality in commercial real estate markets. This research can generally be separated into two main camps in terms of the different market context they focus on.

2.1 Seasonality in capital markets and explanation for January effect

Since 1960's, abundant research has concentrated on the existence of seasonality in capital markets. Granger and Morgenstern (1963, 1970) apply spectra analysis to examine the question of existence. They conclude that spectral analysis "gave no evidence of a seasonal (12-month) peak in the spectra although small peaks corresponding to seasonal harmonics were quite frequently observed". Bonin and Moses (1974) look for seasonality in the 30 individual Dow-Jones Industrial stocks using monthly price data adjusted for capital changes over the period 1962-1971. The authors use the Census X-11 program and several other criteria- comparisons with other time series and tests on a holdout period – before accepting seasonality. They conclude that 7 of the stocks display significant and persistent seasonal patterns. Officer (1975) conducts the time series methods of Box and Jenkins to study aggregate Australia stock returns over 1958-1970. He finds that a 9-month, 6-month and 12-month seasonal in the autocorrelation function. Michael Rozeff and William Kinney, Jr. (1976) employ various statistical approaches to present evidence on the existence of seasonality in monthly rates of return on the New York Stock Exchange from 1904-1974. Their conclusion is that with the exception of the 1929-1940 period, there are statistically significant differences in mean returns among months due primarily to large January returns. Donald B. Keim (1982) examines, month-by-month, the empirical relation between abnormal returns and market value of NYSE and AMEX common stocks. The results show that daily abnormal return distributions in January have large means relative to the remaining eleven months.

Several hypotheses have been suggested to explain the January seasonal in stock returns. Most prominent are a tax loss selling hypothesis and an information hypothesis. Branch (1977) formulates an explanation for disproportionately large January returns based on year-end tax loss selling of shares that have declined in value over the previous year. Keim (1982) presents evidence indicating that large abnormal returns recorded in the first five trading days of January are associated with low-priced shares with the smallest market value portfolio. Roll (1982) argues that the annual pattern in small firm returns is strongly associated with tax loss selling, and conjectures that large transactions costs for smaller firm shares prevent arbitragers from eliminating the large abnormal returns in the first few days in January. Rozeff and Kinney (1976) note that January marks the beginning and ending of several potentially important financial and informational events. Thus, at least for those firms with year-end fiscal closings, the month of January marks a period of increased uncertainty and anticipation due to the impending release of important information.

2.2 Seasonality in housing markets and explanation for summer peak

Research suggests that some human seasonal behavior patterns have strong effects on the seasonal change of housing price and transaction volume. Chinloy (1999) found that the housing real estate market displays pronounced seasonal returns, with returns to housing markets higher in the summer months. Kuo (1996) proposes a two-step, two-sample method and a Bayesian method to estimate the serial correlation and the seasonally of the price behavior of the residential housing market. The empirical results based on the Bayesian approach reject the random-walk hypothesis in the real estate market. He finds that seasonality is not statistically significant; however, there is still a clear indication that the returns associated with seasonal dummies are strongest in the second quarter, with the first quarter following closely. Kuo concludes that the reason why house prices tend to rise in the spring and summer, fall in the winter, is, in part, that more people want to move into a house in the summer in order that their kids don’t have to change schools in the middle of the school year.

Chapter 3 – Data and Adjustments

3.1 Overview

I examine the transaction volume and capital returns for all properties on MIT's Transaction-Based Index of Institutional Commercial Property Investment Performance (TBI) from the first quarter of 1984 through the fourth quarter of 2005 and capital returns for each type of property for the first quarter of 1994 through the first quarter of 2006. The TBI has developed by the MIT/CRE CREDL Initiative. The purpose of this index is to measure market movements and returns on investment based on transaction prices of properties sold from the NCREIF Index database. The basic TBI represents transaction prices that reflect variable liquidity in the real estate marketplace over time.

3.2 The Differences between TBI and Other Real Estate Price Indices

The TBI is a new type of index that offers advantages for some purposes over the median-price or appraisal-based indexes previously available for commercial real estate in the U.S. Median price indexes are not true price-change indexes because the properties that transact in one period are different from those that transacted in the previous period. Appraisal-based indexes are based on appraisal estimates rather than actual prices of actual transactions. However, it should be noted that TBI is statistical product that can contain estimation error.

3.3 The Adjustments to MIT's TBI

In the third quarter of 2004, NCREIF's NPI changed the rules of recognition on the closing date of transaction deal from previous quarter to current quarter. Because the MIT's TBI is based on NCREIF's data, to analyze apples to apples, I did the adjustment on transaction volume and price index on all properties in TBI before third quarter of 2004: moving every quarter's data towards next quarter and combining the value in second quarter of 2004 and in third quarter of 2004 in MIT's TBI together as the observations I use in this paper.

Figure 1-6 show the historical data of transaction volume and capital returns on all properties from 1984 to 2005 and capital returns on each type of commercial real estate property from 1994 to 2005, which can give me an intuitionistic perception on the market trend by quarter. From Fig. 1, for transaction volume, third quarter obviously has greater value than the rest quarters. From Fig. 2, for capital returns on all properties, fourth quarter generally has higher returns than other three quarters.

Figure 1. Transaction Volume by Quarter

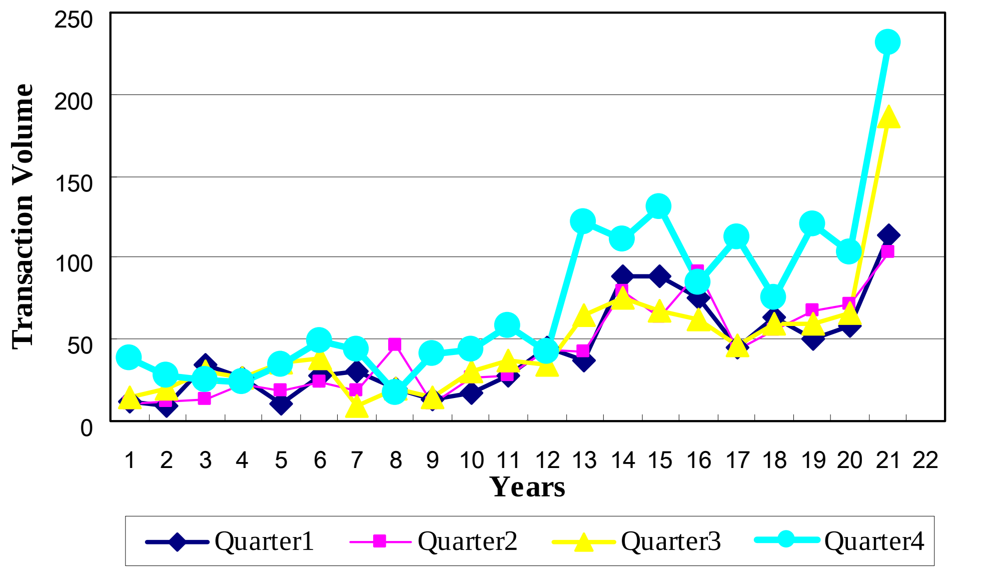


Figure 2. Capital Returns on All Properties by Quarter

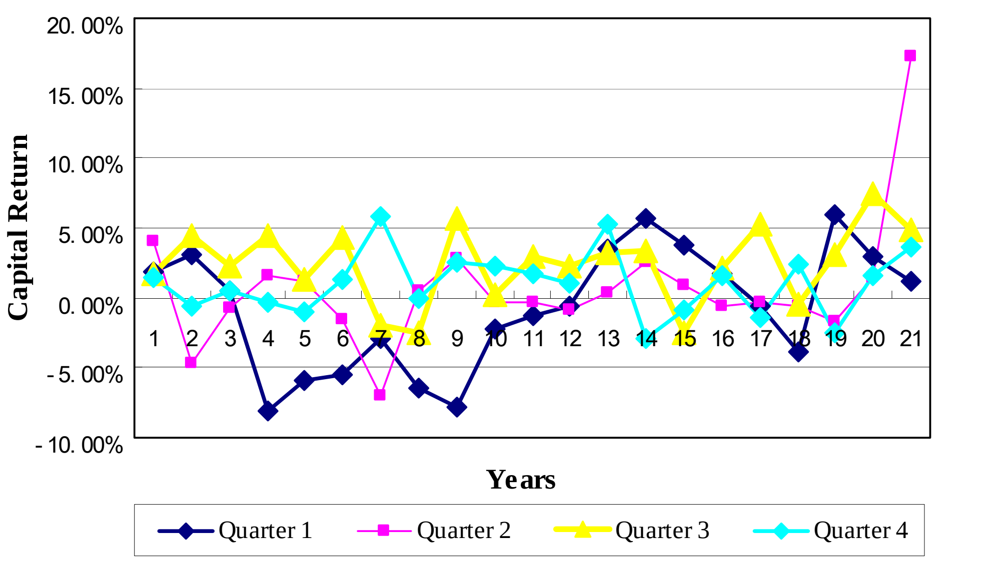


Figure 3. Capital Returns on Apartment markets by Quarter

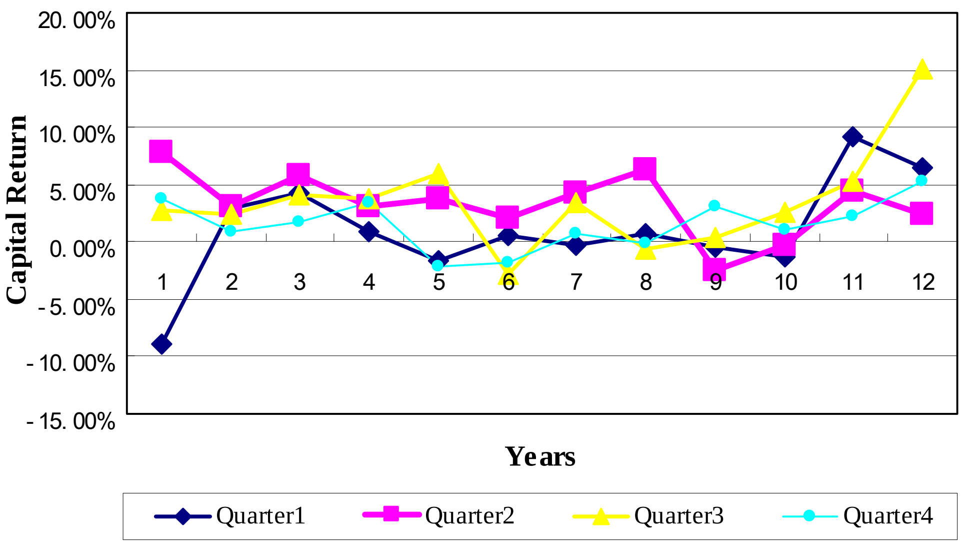


Figure 4. Capital Returns on Industrial Markets by Quarter

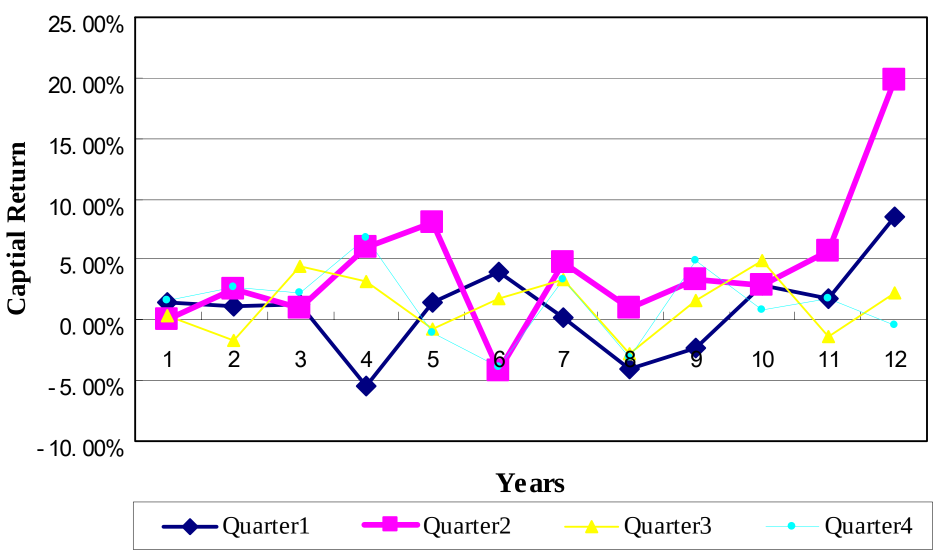


Figure 5. Capital Returns on Office Markets by Quarter

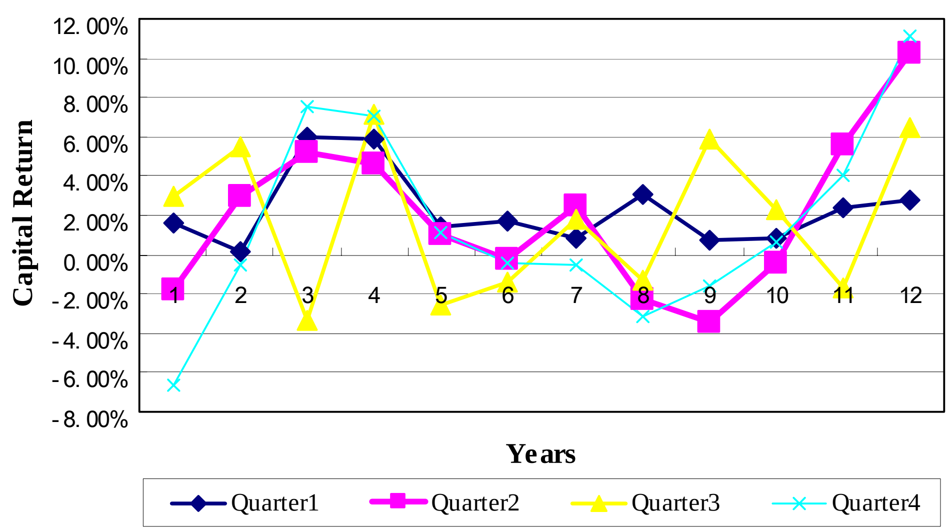
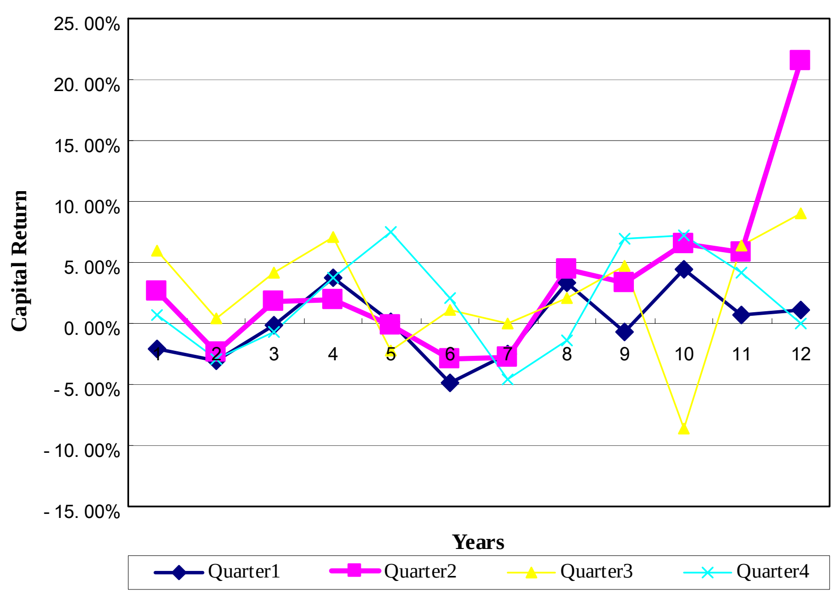


Figure 6. Capital Returns on Retail Markets by Quarter



Chapter 4 – Methodology and Statistics Results

4.1 Randomness Test

First of all, because most standard statistical tests depend on randomness and the validity of the test conclusions is directly linked to the validity of the randomness assumption, it is reasonable for me to examine the randomness assumption in our data sets before applying other statistical tests.

Autocorrelation plots (Box and Jenkins, pp. 28-32) are a commonly-used tool for checking randomness in a data set. This randomness is ascertained by computing autocorrelations for data values at varying time lags. If random, such autocorrelations should be near mean for any and all time-lag separations. If non-random, then one or more of the autocorrelations will be significantly different from mean.

Autocorrelation is a correlation coefficient across time. However, instead of correlation between two different variables, the correlation is between two values of the same variable at times X_i and X_{i+k}. A lag plot checks whether a data set or time series is random or not. Random data should not exhibit any identifiable structure in the lag plot. Non-random structure in the lag plot indicates that the underlying data are not random.

Another important reason why I conduct this approach is that autocorrelation plots are a helpful test to examine the hypothesis that there exists a consistent seasonal pattern across the whole period.

The autocorrelation functions for transaction volume and capital returns on all properties and each type of commercial real estate property are presented in Figure 7-12. Two standard errors from the mean of the estimated autocorrelation coefficients [see Box and Jenkins (1970, p.34)]are set as 95% significant level, which are shown by the solid horizontal lines on either side of each mean. Any coefficient outside of this range is deemed not to be random.

Figure 7. Trans. Volume_Autocorrelation (Lag-12)

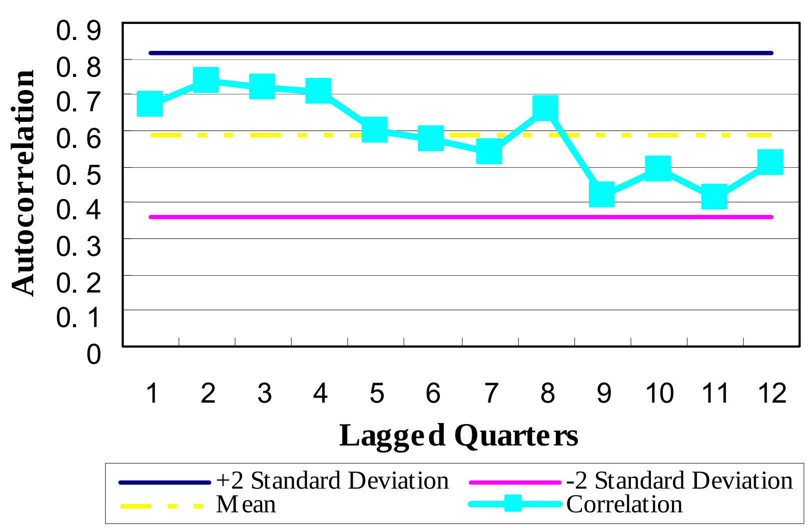


Figure 8. Capital Returns for All Properties_Autocorrelation (Lag-12)

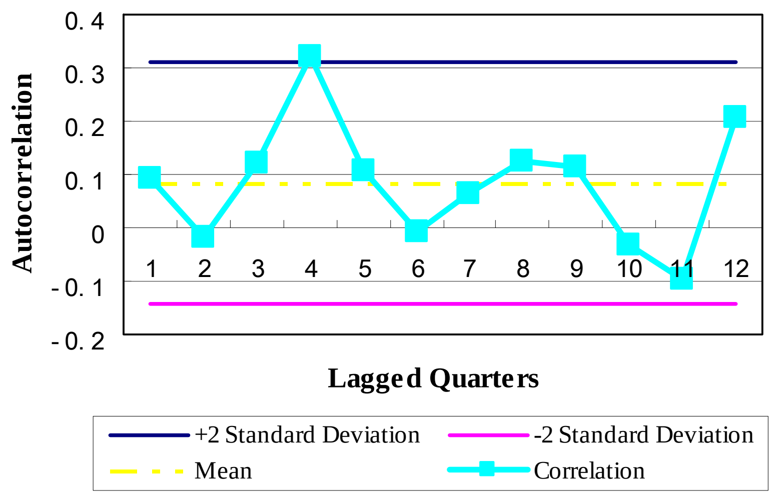


Figure 9. Capital Returns on Apartment Markets_Autocorrelation (Lag-12)

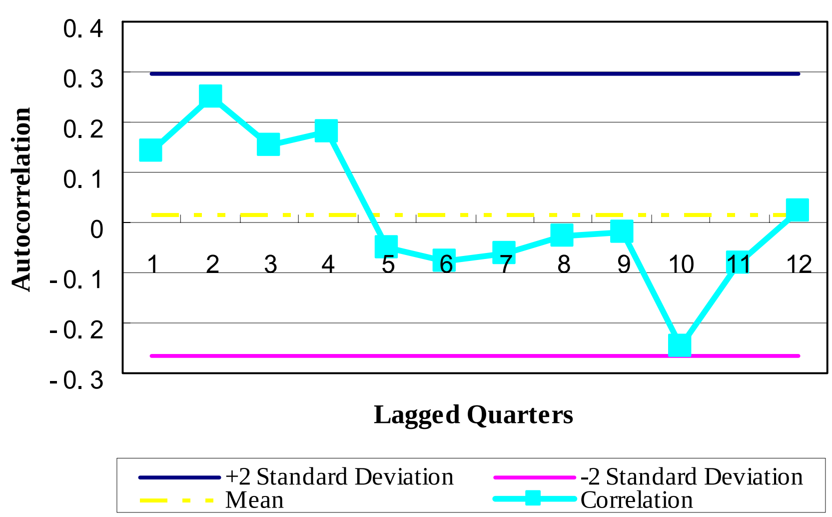


Figure 10. Capital Returns on Industrial Markets_Autocorrelation (Lag-12)

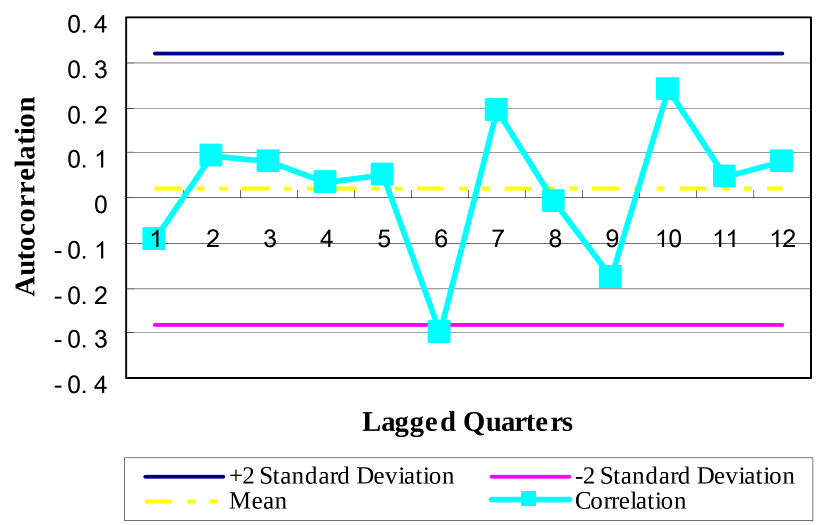


Figure 11. Capital Returns on Office Markets_Autocorrelation (Lag-12)

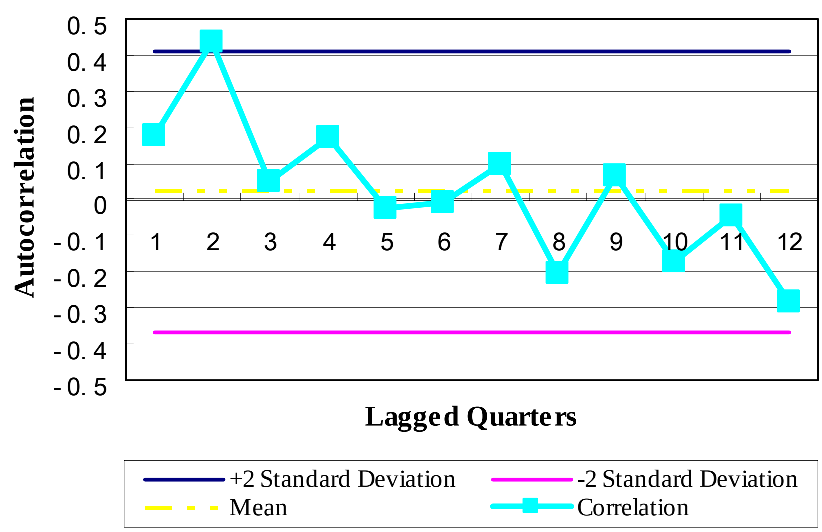
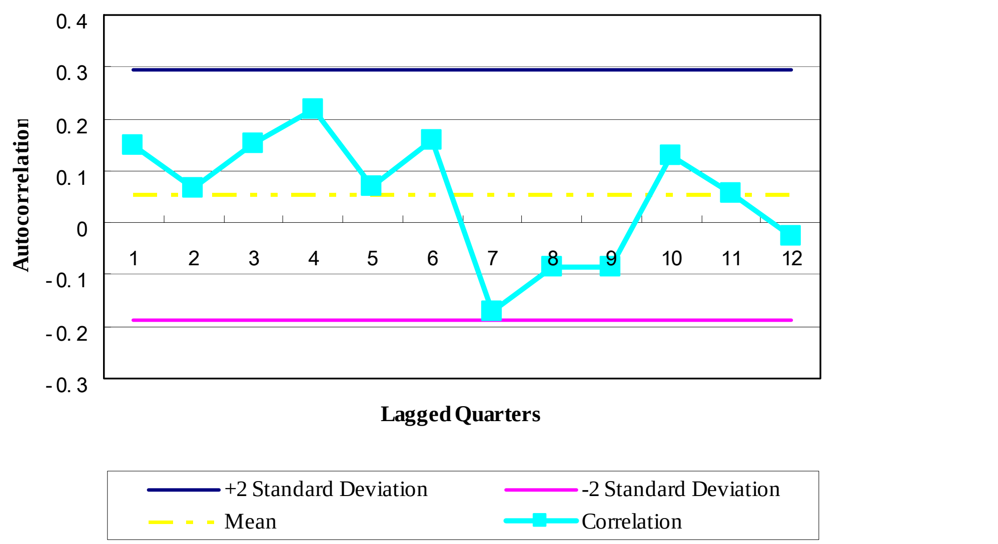


Figure 12. Capital Returns on Retail Markets_Autocorrelation (Lag-12)



The significant levels of individual lags in the autocorrelation function depend to some extent on the time period used as possible business circle horizon. Accordingly, given the lack of knowledge about the business circle horizon about each type of commercial real estate, we must interpret the significant levels with some caution. Given this warning, we see that sample autocorrelation is significant at lag 4 for capital returns on all properties (see Fig.8), at lag 6 for those on industrial markets (see Fig.10), and at lag 2 for those on office markets (see Fig.11), when choosing 12 as the number of the total lagged quarters. Considering the power of autocorrelation function on explaining the systematic homogeneous cyclicality, we can safely conclude that there exists a systematic seasonality in capital returns on all properties. As to capital returns on industrial and office markets, since the sample size is very small, just half of the sizes of transaction volume and capital returns on all properties, the results are not persuadable until more statistical tests are conducted on them.

For transaction volume and capital returns on apartment and retail markets, as opposed to capital returns on office markets, no autocorrelations are more than two standard deviations from their means, indicating a random walk model with no consistent seasonal effects.

The sample autocorrelation function is good at uncovering systematic homogeneous cyclicality between quarters but might fail to reveal peculiarities of individual quarters (or even pairs, triples, etc. of quarters) if the remaining quarters display no relationship. Furthermore, the sample autocorrelation function provides no direct evidence about the distributions of transaction volume and capital returns by quarter. Thus, in the next several subsections, I establish the statistical models and conduct the descriptive statistics test and non-parametric test to examine various hypotheses related to transaction volumes and capital returns by quarter. Those tests can be interpreted as tests for seasonality in the sense that some quarter(s) have different distributions than other quarters.

4.2 Statistical Model

By now, we can safely assume commercial real estate transaction volume and price behaviors (except those in office markets) can be described by random walk models,

$$V_t = m + v_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$R_t = y + w_t \text{..}(2)$$

where v_t and w_t are independent and identically distributed with mean zero. Then, in order to reflect seasonal, we assume that v_t and w_t are independently distributed random variables whose distributions differ only in location parameter[2] by season. Letting subscript *q* denote the quarter of the year, these alternative models are

$$V_{tq} = m + v_{tq} \text{..}(3)$$
$$R_{tq} = y + w_{tq} \text{..}(4)$$

Letting $E(v_{tq}) = l_q$ and $E(w_{tq}) = s_q$, these can be written

$$V_{tq} = m + l_q + v_t \text{.................................... ...}(5)$$
$$R_{tq} = y + s_q + w_t \text{...}(6)$$

where v_t and w_t are again independent and identically distributed with mean zero.

We test the null hypotheses that expected transaction volume and capital returns in quarter of the year are equal, that is,

$$H_0 : E(V_1) = E(V_2) = E(V_3) = E(V_4) = m \text{.......................}(7)$$
$$H_0 : E(R_1) = E(R_2) = E(R_3) = E(R_4) = y \text{.......................}(8)$$

The error terms, v_{tq} and w_{tq} in (3) and (4) may differ in scale measures[3] as well as

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[2] Location parameters measure the center or middle of a distribution. The most common are the mean, median, and mode among many location parameters.

[3] Scale measures are important for describing the spread of the data, or its variation around a central value. Two distinct samples may have the same mean or median, but completely different levels of variability, or vice versa. A proper description of a set of data should include both of these characteristics. There are various methods that can be used to measure the scale of a dataset, including the range, average deviation, variance, and standard deviation. The standard deviation is most commonly used measures of dispersion.

location measures. We therefore test the following hypothesis:

$$H_0 : d_1 = d_2 = d_3 = d_4 = d \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(9)$$

that dispersion parameters, d_i, of trading volume and capital return distributions do not differ by quarter.

4.3 Sample statistics

Sample statistics of transaction volume and capital return distributions calculated by quarter are plotted in Figures 13-18 and summarized in Tables 1-6, including 1) three location measures (see panels a-c): the arithmetic mean, the median and the 75% truncated mean[4] as well as 2) scale measures (see panels d-e): standard deviation and the statistic e and 3) Shapiro-Wilk W test[5], the most powerful among various methods for normality test (see panel f): *p* value. Through presenting these descriptive statistics, we can identify those potential significant differences among the samples.

From panels a-c in Table 1-6, we can obviously see some interesting feature of these statistics, for example, much larger transaction volume in fourth quarter than in the rest of three quarters and significantly higher capital returns on all property in third quarter than in the rest of three quarters.

[4] The 75% truncated sample mean is the arithmetic average of the middle 75% of the observations ordered from smallest to largest, which is probably the most efficient location estimator.

[5] Various methods are provided as part of the continuous descriptive test to determine whether the observations of a sample are normally distributed. The methods are useful in particular circumstances, but the Shapiro-Wilk W test is generally the most powerful. All methods compute a p-value, low p-values indicate sample is non-normally distributed.

Panels d-e contain two scale measures: standard deviation and the statistic e, defined as dispersion measure. For these scale measures, the differences among quarters generally are consistent as for the location measures. Statistic e is regarded as the most stable dispersion measure. The sample standard deviations by quarter are not wildly erratic in comparison with the order statistic e. In all the tables, the orderings of quarters from high dispersion to low which are achieved by e and by standard deviation are highly correlated. This feature of the data is particularly important if we are to have confidence in the parametric analysis of variance tests which rely on the standard deviation as a dispersion measure.

Finally, panel f contains *p*-values of Shapiro-Wilk W test measuring sample normality. Departures from normality are evident as indicated by *p*-values < 0.05. This finding is very important because normality is one of four assumptions for parametric tests, as opposed to non-parametric tests.

In the next subsections the location and scale hypothesis [eqs.(7) ,(8)and (9)] are tested using non-parametric[6]. The reason why I do not employ parametric tests, which is more powerful than corresponding non-parametric tests is that according to the results generated from Shapiro-Wilk W test (*p*-values < 0.05), the samples are not

[6] Nonparametric methods are procedures that work without reference to specific parameters and most appropriate when the sample sizes are small. For every parametric test there is a nonparametric analogue that allows some of the assumptions of the parametric test to be relaxed. The one-sample t test, a parametric method, for example, requires that the observations be drawn from a normally distributed population, while its corresponding non-parametric test, called Kruskal-Wallis test, does not need such an assumption.

normal distributions, which does not meet the assumption for parametric test.

In comparison statistical tests that make few or no assumptions about the distribution of the observations are known as distribution-free or non-parametric tests. Non-parametric tests are usually less powerful than their parametric equivalents, but

are useful when the requirements of the parametric test cannot be met, for example because observations can only be measured on a categorical scale, the sample-size is small, or the distributional assumptions do not hold. So, we begin with the non-parametric tests due to its nature of distribution-free.

Figur 13. Descriptive statistics for transaction volume

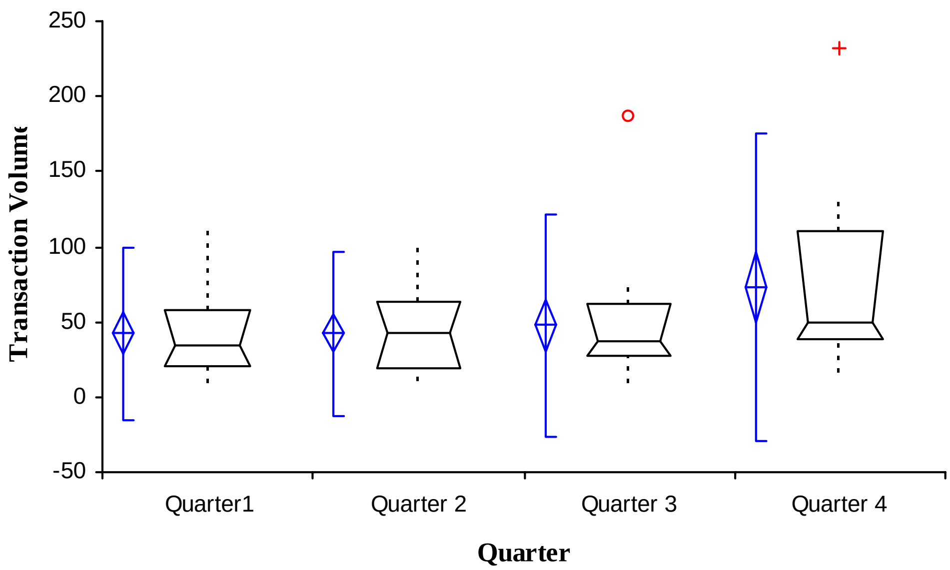

Table 1. *Summary descriptive statistics for transaction volume*

Period	Quarter 1st	2nd	3rd	4th
Location measures				
a. Mean	42.571	42.381	47.619	73.190
b. Median	35.000	42.000	37.000	49.000
c. 75% Trunc. Mean	35.429	36.000	40.286	56.714
Scale measures				
d. Std. dev.	29.245	27.940	37.725	52.242
e. Statistic e	6.382	6.097	8.232	11.400
Shapiro-Wilk W test				
f. *p*-value	0.047	0.059	<0.0001	0.004

Figure 14. Descriptive statistics for capital returns on all properties

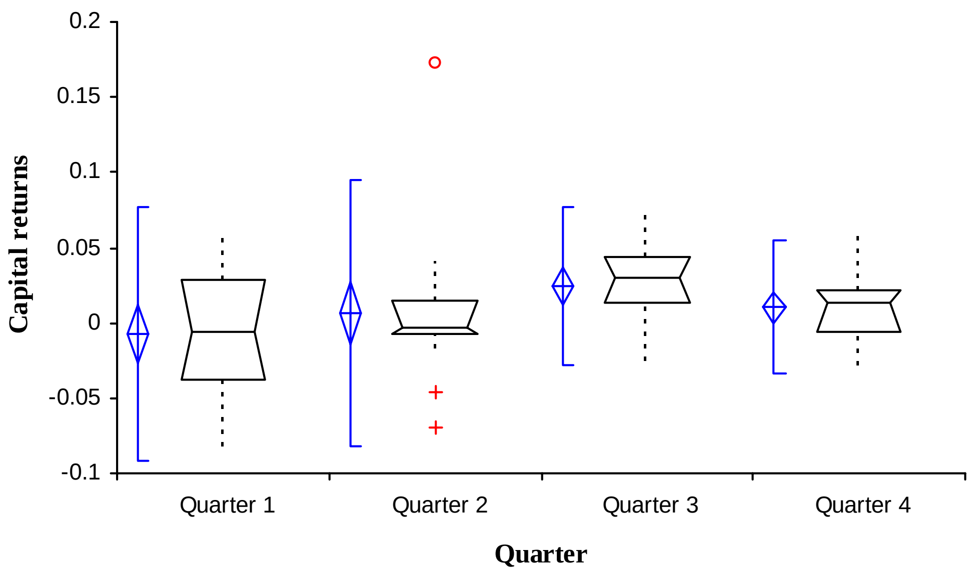

Table 2. *Summary descriptive statistics for capital returns on all properties*

Period	1st	2nd	3rd	4th
	Quarter			
Location measures				
a. Mean	-0.725%	0.670%	2.453%	1.036%
b. Median	-0.635%	-0.321%	2.993%	1.362%
c. 75% Trunc. Mean	-0.180%	0.025%	2.758%	1.086%
Scale measures				
d. Std. dev.	4.328%	4.506%	2.700%	2.259%
e. Statistic e	0.944%	0.983%	0.589%	0.493%
Shapiro-Wilk W test				
f. *p*-value	0.394	<0.0001	0.438	0.773

Figure 15. Descriptive statistics for captial returns on apt. mkt.

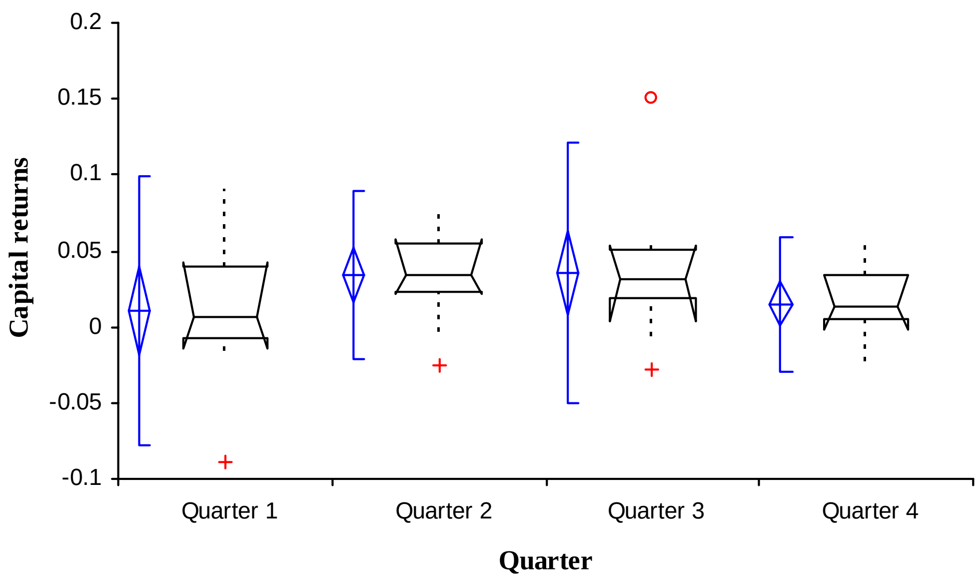

Table 3. Summary descriptive statistics for capital returns on apt. mkt.

	Quarter			
Period	1st	2nd	3rd	4th
Location measures				
a. Mean	1.031%	3.359%	3.525%	1.511%
b. Median	0.687%	3.467%	3.117%	1.402%
c. 75% Trunc. Mean	0.477%	3.560%	3.144%	1.491%
Scale measures				
d. Std. dev.	4.510%	2.822%	4.396%	2.249%
e. Statistic e	1.302%	0.815%	1.269%	0.649%
Shapiro-Wilk W test				
f. *p*-value	0.491	0.850	0.049	0.944

Figure 16. Descriptive statistics for capital returns on ind. mkt.

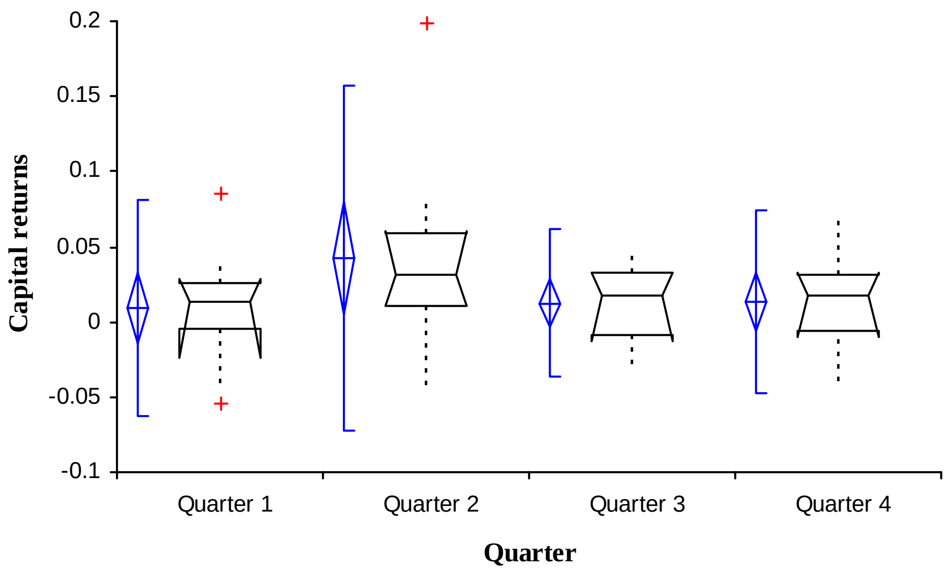

Table 4 *. Summary descriptive statistics for capital returns on ind. mkt.*

	Quarter			
Period	1st	2nd	3rd	4th
Location measures				
a. Mean	0.900%	4.240%	1.254%	1.321%
b. Median	1.356%	3.089%	1.695%	1.725%
c. 75% Trunc. Mean	1.344%	3.366%	1.492%	1.630%
Scale measures				
d. Std. dev.	3.683%	5.862%	2.525%	3.109%
e. Statistic e	1.063%	1.692%	0.729%	0.898%
Shapiro-Wilk W test				
f. *p* -value	0.466	0.038	0.785	0.983

Figure 17. Descriptive statistics for capital returns on off. mkt.

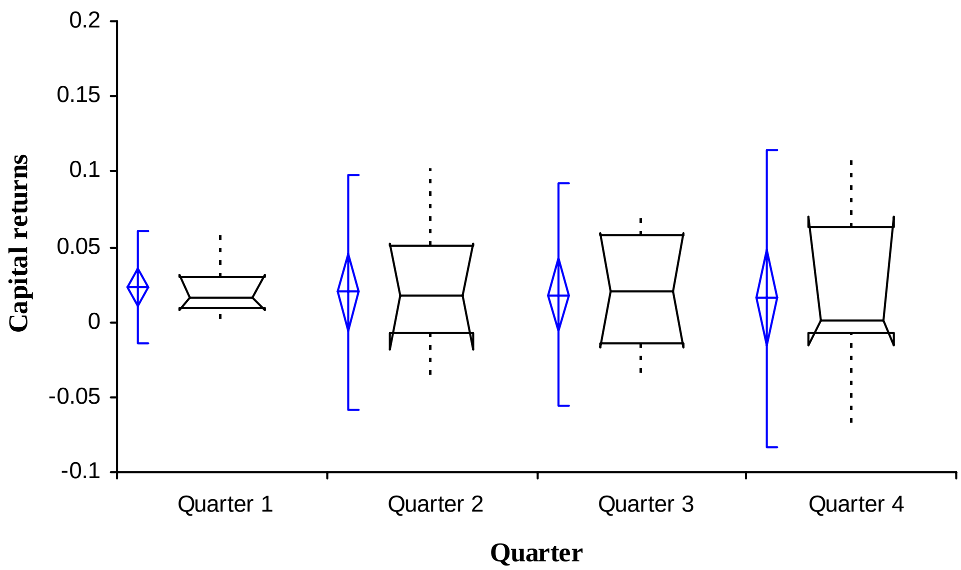

Table 5 *. Summary descriptive statistics for capital returns on off. mkt.*

	Quarter			
Period	1st	2nd	3rd	4th
Location measures				
a. Mean	2.288%	1.986%	1.811%	1.555%
b. Median	1.662%	1.735%	2.048%	0.082%
c. 75% Trunc. Mean	1.781%	1.535%	1.446%	0.205%
Scale measures				
d. Std. dev.	1.899%	3.968%	3.790%	5.014%
e. Statistic e	0.548%	1.146%	1.094%	1.447%
Shapiro-Wilk W test				
f. *p* -value	0.031	0.761	0.181	0.647

Figure 18. Descriptive statistics for capital returns on ret. mkt.

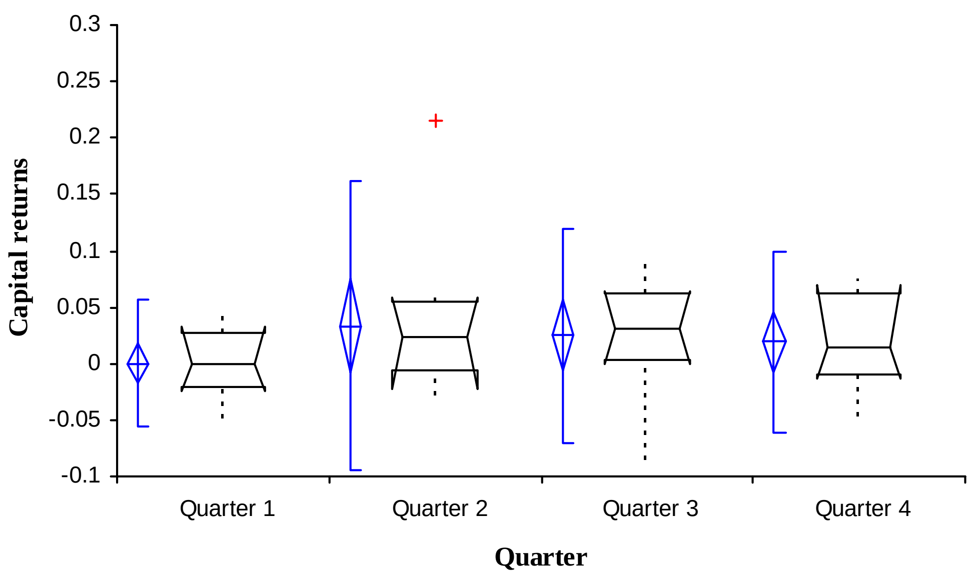

Table 6 *. Summary descriptive statistics for capital returns on ret. mkt.*

	Quarter			
Period	1st	2nd	3rd	4th
Location measures				
a. Mean	0.028%	3.339%	2.517%	1.896%
b. Median	-0.010%	2.326%	3.132%	1.432%
c. 75% Trunc. Mean	0.024%	2.434%	3.010%	1.645%
Scale measures				
d. Std. dev.	2.862%	6.542%	4.835%	4.076%
e. Statistic e	0.826%	1.888%	1.396%	1.177%
Shapiro-Wilk W test				
f. *p*-value	0.916	0.007	0.476	0.591

4.4 Non-parametric tests

The Kruskal-Wallis test statistic, fully described in Conover (1971, p. 157), is a test which uses “rank” and requires no distributional assumptions other than the random variables are continuous and measurable on an ordinal scale. The Kruskal-Wallis test statistic is used to test the hypothesis that all 4 of the populations from which the 4 samples are drawn have identical population distributions.[7] The test statistic is approximately distributed as chi-square[8] with 3 degrees of freedom, which value is

[7]Since the Kruskal-Wallis statistic is designed to be sensitive to differences in population means, the test may more loosely be regarded as testing the hypothesis that all the distributions have identical means.

[8]Kruskal and Wallis found that for 10% significant levels or less, the true significant level is smaller than that given with the chi-square distribution [see Conover (1971). In other words, the chi-square gives a conservative hypothesis test.

7.81 at 5% significant level or 6.25 at 10% significant. [9]

Table 7. *Summary non-parametric test statistics*

category	Kruskal-Wallis statistic	*p* -value
Transaction volume	6.52[a]	0.089
Capital returns on		
all properties	9.47[b]	0.024
apartment markets	4.60	0.204
industrial markets	3.50	0.321
office markets	0.85	0.839
retail markets	3.59	0.310

[a] Significant at the 0.90 level.
[b] Significant at the 0.95 level.

The results are shown in Table 7. For transaction volume the null hypothesis can be rejected at the 10% level; for capital returns on all properties, the hypothesis can be rejected at the 5% level. In contrast, for capital returns on each type of property, there are no *p* values bigger than the benchmark, value of Chi-square at 10% significant level, which means we cannot reject the null hypothesis. Given the conservative nature of the test, this is rather convincing evidence for seasonality in transaction volume and capital returns on all properties, in that at least one of the population distributions from which the samples are drawn differs from some the rest in location. In contrast, the autocorrelation function gave no signs of seasonality in transaction volume.

[9] These value was generated using the Stata function invchi.

Furthermore, in order to find the quarters that are responsible for the results, we conduct multiple pairwise comparisons among quarters using the rank sums for each quarter and investigating the differences in rank sums, which is due to Harley (1955) as well as Wilcoxon and Wilcox (1964).

Table 8 . *Connover pairwise commparisons for transaction volume*

Connover Contrast	Difference	*p*- value
Quarter1 v Quarter 2	-0.024	0.997
Quarter1 v Quarter 3	-3.214	0.663
Quarter1 v Quarter 4	-16.476	0.028
Quarter 2 v Quarter 3	-3.190	0.666
Quarter 2 v Quarter 4	-16.452	0.028

Table 9 . *Connover pairwise commparisons for returns on all properties*

Connover Contrast	Difference	*p*- value
Quarter1 v Quarter 2	-1.190	0.869
Quarter1 v Quarter 3	-20.619	0.005
Quarter1 v Quarter 4	-7.810	0.282
Quarter 2 v Quarter 3	-19.429	0.009
Quarter 2 v Quarter 4	-6.619	0.362
Quarter 3 v Quarter 4	12.810	0.080

In Tables 8-9, panel a contains rank sums and mean ranks in each quarter for transaction volume and capital returns on all properties; the differences and *p* values for each pairwise contrast are shown in panel b. After comprehensively reviewing all the results, we find that for transaction volume, fourth quarter has a significantly greater mean rank than first quarter and second quarter at 5% level as well as third quarter at 10% level; for capital returns on all properties, likewise, mean rank in third quarter is significantly greater than that in first quarter and second quarter at 1% level as well as in fourth quarter at 10% level.

In summary, seasonality in commercial real estate transaction volume and capital returns on all properties is a statistically significant phenomenon that is clearly observable when the data are examined by quarter. At least one distribution is different from the rest as shown by Kruskal-Wallis test. The pairwise tests indicate that relatively large transaction volume in fourth quarter and high capital returns in third quarter are likely the source of the distributional difference.

Further, to exhaust the methods to test the seasonality, I employ the time dummy variable models in next subsection to examine the significant levels of the intercept coefficients and slope coefficients.

4.5 Time dummy variable model

To obtain a somewhat better sense of the possible seasonal behavior of transaction volume and capital returns which might appear in various statistical tests above, we run the following regressions,

$$V_t = b_1+b_2D_1+b_3D_2+b_4D_4+v_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

$$R_t = y_1+y_2D_1+y_3D_3+y_4D_4+w_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

where D_1 through D_4 is a set of dummy variable representing the quarters of the year from Spring through Winter. The intercepts, b_1 and y_1, measure the mean transaction volume in fourth quarter and the mean capital returns in third quarter, respectively. The regression equations examine whether or not the intercept coefficients, b_1 and y_1, are significant and the dummy variables are significant different from fourth quarter and third quarter, respectively.

The regression outputs for transaction volume and capital returns on all properties are given in table 10 and table 11, respectively. Through checking the values of *F*-statistics (>2) and *p*-values (<0.05), we find that for transaction volume, only the values of b_1 to b_2 are statistically significant at 1% level and 5% level, respectively, whereas b_2 and b_3 are not. The fact indicates eq. (11) is not an appropriate approach to predict the behaviors of transaction volume. Nevertheless, note that b_2, b_3, and b_4 all have negative sign, indicating the mean transaction volume in fourth quarter is significant greater than in the rest quarters in the year. Likewise, for capital returns on all properties, y_1 and y_2 are statistically significant at 1% level, while y_3 and y_4 seem not to be very significant and third quarter has high capital returns than the rest.

Table 10 *. Summary output of dummy variable model for transaction volume*

a. analysis of variance

Source of variation	SSq	DF	MSq	*F*	*p* -value
Due to regression	8531.581	3.000	2843.860	1.362	0.260
About regression	179567.974	86.000	2088.000		
Total	188099.556	89.000			

b.regression output

Term	Coefficient	SE	*p* -value	95% CI of	Coefficient
Intercept	70.364	9.742	<0.0001	50.997	to 89.730
D1	-25.955	13.777	0.063	-53.343	to 1.434
D2	-20.146	13.627	0.143	-47.236	to 6.943
D3	-19.929	13.627	0.147	-47.018	to 7.160

Table 11 *. Summary output of dummy variable model for returns on all properties*

a. analysis of variance

Source of variation	SSq	DF	MSq	*F*	*p* -value
Due to regression	0.009	3.000	0.003	2.208	0.093
About regression	0.109	83.000	0.001		
Total	0.118	86.000			

b.regression output

Term	Coefficient	SE	*p* -value	95% CI of	Coefficient
Intercept	0.023	0.008	0.003	0.008	to 0.039
D1	-0.028	0.011	0.012	-0.050	to -0.006
D2	-0.017	0.011	0.137	-0.039	to 0.005
D4	-0.015	0.011	0.166	-0.037	to 0.006

Chapter 5 – Conclusion and Future Research

5.1 Conclusion

Based on the adjusted data in MIT's TBI, seasonality in transaction volume and capital returns on all commercial properties becomes clearly evident once the observations are tested by comparative descriptive statistics and a non-parametric statistical test. The most outstanding features of the seasonality are 1) four quarters lagged systematic seasonality in capital returns on all properties, 2) the greater mean of transaction volume distribution in fourth quarter and 3) the higher mean of capital returns distribution in third quarter, compared with the rest quarters in the year.

5.2 Future Research

Hypotheses which seek to explain seasonality and the non-synchronization between transaction volume and capital returns are not tested in this paper. Our main purposes are to demonstrate their existence. Nevertheless, I provide a few of potential options as the avenues of exploration for the future research as follows:

(1) tax-selling hypothesis: to capture the tax deduction benefits at year-end, investors might be willing to sell the properties with previous three-quarter price declines, which could also explain why the heavy transaction volume did not result in an abnormal rise of price.

(2) price-discovery hypothesis: market participants might be encouraged by large transaction volume in fourth quarter to eagerly search ideal deals in the markets, and then these collective behaviors could cause the rise on demand and, accordingly, the rise on commercial real estate prices. For example, from Figs. 1 and 2, in Yr 1, fourth quarter has largest transaction volume; in Yr 2, third quarter has greatest capital returns on all properties, and the same situation takes place in Yr 5 – Yr6, Yr 10 – Yr 11, Yr 11 – Yr12, Yr 15 – Yr 16, and Yr 19 – Yr 20.

References

Armitage P., Berry G., 1994, *Statistical Methods in Medical Research (3rd Edition)*, 14-40

Bonin, J.M and E.A. Moses, 1974, Seasonal variations in prices of individual Dow-Jones industrial stocks, *Journal of Financial and Quantitative Analysis* 9, 963-991.

Box. G.E.P. and G. Jenkins, 1970, Time series analysis, forcasting and control (Holden-Day, San Francisco, CA).

Branch, B., 1977, A tax loss trading rule, *Journal of Business* 50, 198-207.

Chinloy, P., 1999, Housing, illiquidity, and Wealth, *Journal of Real Estate Finance and Economics* 19, 69-83

Chiong-Long Kuo, 1996, Serial correlation and seasonality in the real estate market, *Journal of Real Estate Finance and Economics* 3, 139 – 162

Conover, W.J., 1971, Practical nonparametric statistics (Wiley, New York).

Fisher. J., Gatzlaff. D., Geltner. D. & Haurin. D., 2003, Controlling for the Impact of Variable Liquidity in Commercial Real Estate Price Indices, *Journal of Real Estate Economics* 31:2, 269

Fisher. J., Geltner. D., & Pollakowski. H., 2006, A quarterly transactions-based index of institutional real estate investment performance and movements in supply and demand, Working paper (MIT Center for Real Estate)

Granger. C.W.J. and O. Morgenstern, 1963, Spectral analysis of New York stock market prices, *Kyklos* 16, 1-25.

Granger. C.W.J. and O. Morgenstern, 1970, Predictability of stock market prices (D.C. Heath and Co., Lexington, MA).

Keim, D.B., 1980, Further evidence on size effects and yield effects: The implications of stock return seasonally, Unpublished manuscript (University of Chicago, Chicago, IL).

Keim, D.B., 1983, Size-related anomalies and stock return seasonality: Further empirical evidence *Journal of Financial Economics* 12, 13-32.

Officer, R.R., 1975, Seasonality in Australia capital markets: Market efficiency and empirical issues, *Journal of Financial Economics* 2, 29-51.

Roll, R., 1982, The turn of the year effect and the return premia of small firms, Working paper (Graduate School of Management, University of California, Los Angeles, CA).

Royston P., 1992, Approximating the Shapiro-Wilk W test for Non-Normality. *Statistics and Computing* 2:117-119.

Rozeff, M.S. and W.R. Kinney, Jr., 1976, Capital market seasonality: The case of stock returns, *Journal of Financial Economics* 3, 379-402.

Shapiro, S. S. and Wilk, M. B. (1965). "An analysis of variance test for normality (complete samples)", *Biometrika*, 52, 3 and 4, 591-611.

Siegel S., Castellan Jr N.J., 1988, *Non-parametric Statistics for the Behavioral Sciences (2nd Edition)*, 174-83.

Strike P.W., 1991, Statistical methods in Laboratory Medicine, 96-128.