Bulletproof Cities: Geography of the Systematic Risk in Commercial Real Estate Investments*

Liang Peng
Leeds School of Business
University of Colorado at Boulder
419 UCB, Boulder, CO 80309-0419
Email: liang.peng@colorado.edu
Phone: (303) 4928215

February 2011

Abstract

This paper empirically analyzes the geographical distribution of the systematic risk in U.S. commercial real estate investments, using 3,240 institutional grade properties with detailed cash flow and location information. Overcoming the thin market problem with the Generalized Repeat Sales Regression proposed by Peng (2011), this paper estimates the systematic risk at the Core Based Statistical Areas (CBSA) level and relates it to local economic conditions and land supply constraint. The results indicate that, first, the systematic risk varies dramatically across CBSAs for each of four major property types: apartment, industrial, office and retail properties. A list of CBSAs with low systematic risk - the Bulletproof Cities - emerges from this analysis. Second, the results suggest no correlation between the CBSA systematic risk and local economic conditions or land supply constraints.

JEL classification: C51, G11, G12

Key words: commercial real estate, systematic risk, bulletproof city, Generalized Repeat Sales Regression

* I thank the Real Estate Research Institute (RERI) for a research grant, and NCREIF for providing the data. I am grateful for the constructive comments and suggestions provided by Jim Clayton, Jeffrey Fisher, David Geltner, Gail Haynes, Greg MacKinnon, Asieh Mansour, Martha Peyton, Doug Poutasse, and participants of the 2010 RERI conference. All errors are mine.

I. Introduction

While location is believed to have a significant impact on the *values* of commercial real estate, there is little evidence on its implications on the *risk* in commercial real estate investments. The possible variation in the risk across locations, such as countries, regions, states, and cities, has direct implications on the assessment and management of the risk of real estate portfolios. Since individual properties often constitute non-trivial shares of real estate investors' portfolios (see, e.g., Fisher and Goetzmann (2005), Plazzi, Torous and Valkanov (2008), and Peng (2010), among others, for discussions), portfolios comprising properties in different locations can have distinctive risk characteristics.

This paper analyzes the geographical distribution of the systematic risk in U.S. commercial real estate investments. In this paper, the systematic risk of a property is defined as the sensitivity of the log investment return of the property to the log investment return of an index that tracks the real estate investment performance of the U.S. market. This measurement has the same spirit with the beta coefficient in the capital asset pricing model (CAPM). It is clear that other definitions or measurements of the systematic risk, such as the sensitivity with respect to the stock market performance or GDP, can be sensible as well, but will lead to different papers. This paper defines "location" using the Core Based Statistical Areas (CBSAs). Properties located in the same CBSA are considered as having the same location. Note that we are not arguing that this definition of location is ideal or optimal - the risk might vary across neighborhoods/districts within the same CBSA (see, e.g., Peng and Thibodeau (2012) for evidence regarding the variation of the house price risk across zip codes in Denver). This definition is used because the data in this paper contain reasonably large numbers of properties for many CBSAs in the sample, which allow accurate measurements of the average systematic risk at the CBSA level.

The research questions in this paper are novel as they pertain to the heterogeneity in the risk of commercial real estate investments. The existing literature, on the other hand, usually treats commercial properties as homogeneous and focuses on the average risk of commercial properties as an "asset class". For example, Brueggeman, Chen and Thihodeau (1984) use quarterly data from two comingled real estate funds from 1972 to 1983 to analyze the risk of commercial real estate in the CAPM framework. They find that real estate investment returns have an insignificant market beta and a significant and positive correlation with the inflation rate. Hartzell, Hekman and Miles (1986) analyze the income and appreciation of up to 403 properties from 1973 to 1983, and find an insignificant correlation with the S&P returns, a negative correlation with bond returns, and a positive correlation with the inflation rate. Geltner (1989) un-smoothes the quarterly Frank Russell Company and Prudential Property Investment Separate Account indices to study the risk of commercial real estate in the framework of CAPM, and finds a zero stock market beta and a positive correlation with national consumption. Gyourko and Linneman (1988) analyze the correlation between the inflation rate and the returns of REITs, owner-occupied homes, and direct commercial real estate investments, and find that returns of direct commercial real estate investments are mostly positively related to inflation, while REIT returns are negatively related to inflation. Goetzmann and Ibbotson (1990) use appraisal-based investment returns to find that commercial real estate returns are not related to stock returns, and positively related to interest rates. Ling and Naranjo (1997) analyze the appraisal-based NCREIF national and regional indexes and other measurements to measure direct commercial real estate investments returns. They find a positive loading on consumption growth, and negative loadings on the real T-bill rate, the term spread, and the unanticipated inflation. Peng (2010) proposes a new method to use property level information to more accurately analyze the risk and return characteristics of commercial real estate investments. He finds that commercial real estate risk premium is positively related to GDP growth and the change in the credit spread, and negatively related to inflation, the stock market risk premium, and the change in the term spread. This paper distinguishes itself from the above papers in focusing on the heterogeneity in commercial real estate investment returns, and thus constitutes an important extension to the literature.

This paper presents two original results. First, it provides strong empirical evidence that the systematic risk in commercial real estate investments is location dependent and property type dependent. Specifically, this paper estimates and reports the average systematic risk for each of four property types – apartment, industrial, office, and retail – for each CBSA that contains more than 10 observations of property investments of this type. The results indicate that the average systematic risk for most of the CBSAs is statistically significantly different from 1. Further, the results help identify CBSAs with low systematic risk, which are called Bulletproof Cities. Specifically, the top 5 Bulletproof Cities for apartment properties are Charlotte, NC, Raleigh, NC, Kansas City, MO, Dallas, TX, and Baltimore, MD. The top 5 for industrial properties are Memphis, TN, Edison, NJ, Dallas, TX, Denver, CO, and Fort Lauderdale, FL. The top 5 for office properties are West Palm Beach, FL, Atlanta, GA, Denver, CO, Minneapolis, MN, and Oakland, CA. The top 5 for retail properties are Denver, CO, San Diego, CA, Seattle, WA, Oakland, CA, and Dallas, TX.

Second, this paper finds that the systematic risk in commercial real estate investments for each CBSA is generally not explained by local economic conditions or land supply constraints. Specifically, the local economic conditions are measured with the temporal average and the sensitivity to the national economy of a variety of variables, including the growth rate of the Gross Metropolitan Product (GMP), the growth rate of the per capita GMP, the growth rate of total nonfarm employees, and the unemployment rate. The lack of power of the local economic conditions and land supply constraints in explaining the systematic risk in commercial real estate investments is perhaps puzzling and calls for more theoretical and empirical research in this area.

To our knowledge, the above two results have not been documented in the literature. In fact, the literature is mostly silent on the geographical distribution of the risk of commercial real estate investments. The lack of research is not due to the lack of interests or the lack of importance of this topic; instead, it is mostly due to the lack of data and the lack of suitable econometric methods. First, data on commercial real estate investments that contain location information have been rarely available to academic researchers. Second, the traditional approach to analyze the risk of commercial real estate relies on price indices. For example, to estimate the systematic risk of properties in a specific location, the traditional approach would construct a price index for properties in this location, and then regress the location index against a national index. This approach often works for residential properties due to the reasonably large sample size of transactions (see, e.g., Peng and Thibodeau (2012)), but it hardly works for commercial real estate as the sample size tends to be much smaller for commercial properties and there are small numbers of value observations to construct location specific indices.

This paper overcomes these two challenges. First, the empirical analyses in this paper are based on the National Council of Real Estate Investment Fiduciaries (NCREIF) database, which seems the most comprehensive and accurate database that provides detailed operational, financing, and location information of institutional grade commercial real estate. It is important to note that the database is built to contain all the operational information over the entire holding periods of properties, including not only the acquisition cost, the quarterly net operating income during the holding period, and the net sales proceeds, but also detailed information on capital expenditures, including expenses of renovation and improvements. The detailed information allows accurate measurements of property investment returns. Particularly, it mitigates the biases that are related to changes in property attributes due to renovations and improvements, which are difficult to address in most real estate research due to the lack of information on renovations/improvements.

This paper uses the Generalized Repeat Sales Regression developed by Peng (2011) to estimate the average systematic risk for each CBSA for each of the four property types. This approach does not need to estimate CBSA indices, which is an important feature as it is infeasible to estimate indices for most CBSAs because these CBSAs have fewer investment observations than the quarters in the sample period. This approach directly estimates the average systematic risk for each CBSA, which is just one parameter, using investment observations for that CBSA. Therefore, the degree of freedom in the estimation for each CBSA equals the number of investment observations in that CBSA minus one, which is often sufficient to provide strong results. Applying this simple but powerful econometric method on the NCREIF database, which is likely the most accurate database of commercial real estate investments, allows us to provide convincing results regarding the geographical distribution of the systematic risk in commercial real estate investments in the U.S.

The rest of this paper is organized as follows. Section II discusses the estimation of the systematic risk and the empirical model. Section III discusses the data set and the construction of explanatory variables. Section IV presents the empirical results. Our conclusions are presented in the last section.

II. Research Design

We estimate the average systematic risk at the CBSA level for each of the four property types – apartment, industrial, office, and retail - separately using the Generalized Repeat Sales Regression (GRSR) proposed by Peng (2011). We analyze the property types separately for two reasons. First, as Pivo and Fisher (2011) point out, the weights of different property types in NCREIF database are inconsistent with the weights in the U.S. market. Second, the four property types have different risk return characteristics (see, e.g., Peng (2010) for formal tests).

The GRSR allows the estimation of the average systematic risk for submarkets, which are CBSAs in this paper, even if each submarket has small numbers of investment observations. A key feature of the GRSR that enables this estimation is that the GRSR captures the difference between average investment returns in each submarket and the overall market investment returns with "sensitivity" parameters, and uses each property as an observation to help estimate the parameters. This dramatically differs from the conventional approach that relies on submarket indices to estimate the submarket systematic risk, which becomes infeasible when submarkets have small numbers of sample properties.

To see the distinctions between these two approaches, imagine a CBSA with 40 observations of property investments that span a period of 30 years (120 quarters). The traditional approach would need to use the 40 observations to estimate 119 quarterly CBSA index investment returns (120 quarters minus one base quarter), and then regress the 119 submarket index returns against the 119 national market index returns in the same period. This approach is apparently infeasible due to the lack of degree of freedom in estimating the 119 submarket index returns from 40 observations. The GRSR approach, on the contrary, just needs to estimate one sensitivity parameter (or multiple parameters, depending on the specification of the model) from a regression of the 40 property investment returns against the national market index returns over the respective holding periods of the 40 investment returns.

Specifically, the GRSR assumes that the log of the gross total return of property i from period t to $t+1$, $R_{i,t+1}$, has a national market component, which is the market index $MarketIndex_{t+1}$, and a location specific "sensitivity" parameter, which is the systematic risk τ_{CBSA_i} for the CBSA where property i is located.

$$\log\left(R_{i,t+1}\right) = \tau_{CBSA_i} MarketIndex_{t+1} + \varepsilon_{i,t+1} \tag{1}$$

Two things are worth noting in (1). First, the only difference between the GRSR model in (1) and the conventional RSR is that the conventional RSR forces τ_{CBSA_i} to be 1. Second, it is possible to let τ_{CBSA_i} be a function of variables such as market conditions, but this paper maintains the simplest assumption and focuses on the average local systematic risk of properties in the same CBSA across the sample period.

For sample property investments in this paper, we only know the gross total returns over their respective holding periods, not the periodic returns. Therefore, the GRSR aggregates both the left side and the right side of equation (1) over the holding period, which leads to the relationship between the gross total return (in log) of the property over the holding period and the aggregate value of the market index over the same period.

$$\begin{aligned} \log\left(R_i\right) &= \sum_{t=t_{buy}^i+1}^{t_{sell}^i} \log\left(R_{i,t}\right) \\ &= \tau_{CBSA_i} \sum_{t=t_{buy}^i+1}^{t_{sell}^i} MarketIndex_{t+1} + \sum_{t=t_{buy}^i+1}^{t_{sell}^i} \varepsilon_{i,t+1} \end{aligned} \tag{2}$$

Note that the market index in (2) is unknown. We use two approaches to address this problem. First, we treat the market index returns as a set of parameters that can be estimated in sample. When obtain the in-sample estimates of the market index returns, it is important to note that the market index returns need to be jointly estimated with the CBSA systematic risk parameters. Peng (2011) shows that the market index would be estimated with bias using the conventional RSR if properties have heterogeneous investment returns. The second approach is to use the MIT Transaction Based Indices (TBIs), which is estimated from the NCREIF database using the hedonic regression, as market indices. Since the MIT TBIs cover a much shorter period (1994 to 2009) than the sample properties in this paper, when the MIT TBIs are used, many sample properties are excluded from the regression in (2) due to the lack of corresponding TBI returns for their holding periods. This leads to insufficient observations for many CBSAs for the estimation of the systematic risk. Therefore, the results based on the MIT TBIs only serve as robustness checks, which indeed indicate that the systematic risk estimated using the two market indices are highly correlated.

It is important to note that neither approach is ideal, as they do not weight properties in different CBSAs using the units, the size, or the total market value of properties in each market. Instead, the in-sample estimates of market index returns weight CBSAs based on their numbers of observations in the sample of this paper, and the MIT TBIs weight CBSAs based on the numbers of NCREIF properties in them. Therefore, neither estimate accurately tracks the total value of the national market over time. To weight CBSAs more sensibly, one would need to know the total units, the square footage, or the total market value for each CBSA. Unfortunately, this type of information is currently not available. Therefore, we leave the possible improvement of the results by using more sensible national market indices to future research. Nonetheless, note that while the systematic risk estimated in this paper is not measured against the true market index, our analysis is effective in substantiating the difference in the systematic risk across CBSAs.

When treating market index returns as latent and estimating them in-sample, this paper uses the two-step EM algorithm proposed by Peng (2011) to estimate (2). The first step pools properties from all CBSAs in the sample, holds constant τ_{CBSA_i} for each CBSA, which was estimated from the previous iteration, and estimates (2) to obtain the $\left\{MarketIndex_t\right\}_{t=1}^{T}$. The initial value of τ_{CBSA_i} is set to be 1 for all CBSAs. The second step estimates (2) for each CBSA separately. In each CBSA level regression, $\left\{MarketIndex_t\right\}_{t=1}^{T}$ obtained from step one is treated as known, and

(2) is estimated to obtain τ_{CBSA_i} for the CBSA. The two steps are iterated until both $\left\{MarketIndex_t\right\}_{t=1}^{T}$ and τ_{CBSA_i} for all MSAs converge.

Note that, when we treat the market index returns as parameters and estimating them in-sample, we do not intend to construct market indices. In fact, due to the relatively small sample size and the long sample period (1977 to 2009), multicollinearity sometimes presents in the first step regression of the iteration, and some consecutive quarters cannot be distinguished from each other. That is, while the regression provides an estimate for the aggregate index value over these consecutive periods, the index value for each period cannot be determined. This is because there is no transaction in these periods. However, it is important to note that this does not affect the estimation of the systematic risk. As equation (2) shows, when estimating the risk, it is the aggregate index returns over the holding period that matters.

Also note that some CBSAs have small numbers of observations of property investments, so the systematic risk τ_{CBSA_i} cannot be estimated accurately for them. To overcome this problem, while we keep property investments in all CBSAs to improve the estimation of the national market index, we let τ_{CBSA_i} remain 1 for CBSAs that have fewer than 10 property observations.[1] In our analyses of the relationships between the systematic risk of commercial real estate investments and local economic conditions and land supply, we focus on the CBSAs that have at least 10 investment observations.

After estimating the systematic risk of commercial real estate investments for each of the CBSAs that have at least 10 observations of property investments, we use the following regression to

[1] All results are robust if we slightly vary the number of observations required to estimate τ_{CBSA_i} .

analyze the determinants of the systematic risk of commercial real estate investments at the CBSA level.

$$\tau_n = \alpha + \sum_{k=1}^{K} \beta_k X_n^k + \upsilon_n \tag{3}$$

In equation (3), $\left\{X_n^k\right\}_{k=1}^{K}$ are variables that help affect the risk in CBSA n.

To identify variables that likely affect the location specific systematic risk in commercial real estate investments, note that (see, e.g. Gordon (1962) and many of its variations) investment returns are essentially determined by two factors – the cash flows generated and investors' required returns. For commercial real estate, the former is primarily determined in the space market, particularly the local space market, and the later is determined in the capital market, which is a national/global market. We hypothesize that the location specific systematic risk of commercial real estate is mostly determined by the variation in the local space market, on both the demand and the supply side.

We include three types of variables in (3). The first measures local economic conditions, particularly the sensitivity of local economic activities to the national economy. The second measures the elasticity of supply in the space market. The third is the interactions between the first two types of variables, as the impact of local economic conditions on commercial real estate values depends on the elasticity of supply. We hypothesize that, the more elastic is the supply, the less significant would be the impact of economic conditions on property values, as the supply would adjust quickly to drive values back to a "normal" level.

III. Data

This paper analyzes the systematic risk at the CBSA level using the National Council of Real Estate Investment Fiduciaries (NCREIF) database. The NCREIF is a not-for-profit association that serves the real estate investment industry by collecting, processing, validating and then disseminating information on financing and operation of commercial real estate. The NCREIF database comprises institutional grade commercial properties owned or managed by NCREIF investment managers and plan sponsors in a fiduciary setting. This database has been used in some recent research that analyzes the valuation, risk, and returns of commercial real estate (see, e.g., Pivo and Fisher (2011), Peng (2010), among others).

The NCREIF database used in this paper contains information on physical attributes, cash flows, and transactions of 23,771 properties over the 1977:1 to 2009:3 period. Four main property types - apartment, industrial, office, and retail properties – constitute 22,313 properties in the database. The physical attributes of each property include the property type, year built, gross square feet, street address, and the CBSA where the property is located, etc. The cash flow and transaction information includes quarterly net operating income (NOI) and capital expenditure (Capex) over the holding period, as well as the acquisition cost or the net sale proceeds if applicable. All cash flow and transaction information is on an unlevered basis.

For properties that have been disposed in the sample period and have complete and accurate cash flow information, we calculate the gross total returns over their respective holding periods. First, we denote by $R_{i,t+1}$ the gross total return of property i from period t to $t+1$. Note that the gross total return is determined by not only value appreciation but also cash flows during this period, which include the proceeds from a possible partial sale of the property (Partial), the net operating income (NOI), and the capital expenditure (Capex). Specifically, we define the gross total return as

$$R_{i,t+1} = \frac{NOI_{i,t+1} - Capex_{i,t+1} + Partial_{i,t+1} + Value_{i,t+1}}{Value_{i,t}}, \tag{4}$$

where $Value_{i,t+1}$ is the net sale proceeds the owner would have received if she had sold the property at the end of period $t+1$, with the only exception being that it equals the acquisition price in the acquisition quarter.

Second, we define the gross total return over the entire holding period - from the acquisition period, t^i_{buy}, to the disposition period, t^i_{sell} - as

$$R_i = \prod_{t=t^i_{buy}+1}^{t^i_{sell}} R_{i,t} \ . \tag{5}$$

While the gross total return in each interim period is unknown due to the lack of market value observations between sales, the gross total return over the entire holding period can be calculated and it equals the internal rate of return (IRR) with the power raised to the length of the holding period. Since all cash flows over the holding period, including the acquisition cost, NOI, Capex, Partial, and the net sale proceeds, are known, we can calculate the IRR from the cash flows, and then calculate the gross total return over the entire holding period from the IRR. Note that when calculating the IRRs, there are sometimes multiple solutions. To select a more sensible IRR for each property, we first calculate the geometric average value appreciation per period using the acquisition cost and the final net sale proceeds only, and use it as a benchmark. While this benchmark does not take into account interim cash flows, it captures the value appreciation component of the total return, and thus provides a good guide regarding the sign and magnitude of the actual IRR. After calculating this benchmark for each property, we obtain all the IRR solutions for the property, and then select the number that is closest to the benchmark as the actual IRR.

The analyses in this paper are based on the gross total returns of 3,240 properties that have complete and seemly accurate location and cash flow information, which are selected from the 22,313 properties that belong to the four main property types using the following rules. First, note that most of the properties (about 67%, or 15,000) have not been disposed by 2009:3. Therefore, the investment performance of these properties is not observed. After excluding these properties, as well as a few properties with missing cash flow information, the sample size becomes 7,242. Second, we further clean the 7,242 properties. Specifically, we exclude properties that are the top 1% and the bottom 1% of the distribution of quarterly value appreciation IRR over the holding period (to mitigate errors in acquisition cost or net sale proceeds), the top 1% and the bottom 1% of the distribution of the ratio of average quarterly NOI to acquisition cost (to mitigate errors in NOI), the top 1% of the distribution of the ratio of the average quarterly Capex to acquisition cost (to mitigate errors in Capex). We also exclude properties of which the maximum quarterly Capex is more than 50% of the acquisition cost (to mitigate errors in Capex), and properties that have identical NOI or Capex for more than 10 consecutive quarters. After applying these rules, the sample size becomes 3509. We then calculate the total return IRR for each property, and exclude 133 properties with missing IRR due to the limit of the R function that calculates IRR that it does not work for holding periods longer than 48 periods. Finally, we exclude properties that are the top 2% and the bottom 2% of the total return IRR distribution, to mitigate errors in the IRR calculation due to the presence of multiple solutions. This leads to the final sample of 3,240 properties.

Table 1 summarizes the 3,240 properties in the final sample, which comprise 911 apartment, 898 industrial, 1,012 office, and 419 retail properties. It is apparent that these properties tend to have large size and high values. For the four property types, the average purchase price is about \$24 million, \$15 million, \$37 million, and \$25 million respectively. The average net sale proceeds is about \$30 million, \$18 million, \$46 million, and \$30 million respectively. The average annual total return IRR is respectively 8.26%, 6.61%, 7.43%, and 10.10%, but the IRRs have large standard deviations. To visualize the distribution of the property IRRs, Figure 1 plots the histogram of the quarterly property gross total return IRR over the holding periods for all 3,240 properties. Table 1 also shows that the average holding period is 18 quarters for apartment, office, and retail properties, and 15 quarters for industrial properties.

It is worth noting that the NCREIF sample properties in this paper has advantages but also weaknesses. An important advantage is that the sample properties have detailed and accurate cash flows that allow the calculation of the gross returns. Particularly, the capital expenditures during hold periods are known; therefore, the calculated returns would not be biased upwards. A main weakness of the NCREIF database in general and the final sample in this paper is that they are not random samples from the universe of commercial real estate in the U.S. market. First, properties in the NCREIF database are institutional grade real estate, which means that they tend to have higher values, lower vacancy rates, more stable cash flows, and probably better investment performance than average properties in the U.S. market. Second, the sample properties in this paper have been disposed and have complete cash flow information. If the disposition decision and the reasons why properties have complete information are related to property investment performance, the average performance of the sample properties likely differs from that of other properties in the NCREIF database. The fact that properties analyzed in this paper are not random samples from the universe of commercial real estate may limit the ability to generalize the results in this paper to all properties in the U.S. market; however, it does not affect the internal validity of our result since it does not change the heterogeneity in the systematic risk across CBSAs for the relatively homogeneous sample properties (all being institutional grade, having been disposed, and having complete cash flow information) used in this paper.

We use a variety of variables to measure local economic conditions, including the Gross Metropolitan Product (GMP) growth rate, the per capita GMP growth rate, the growth rate of total nonfarm employment, and the unemployment rate. For each variable in each CBSA, we estimate its temporal average and sensitivity to its national counterpart from a regression of the time series of the variable on its national counterpart. For example, for each CBSA, we run time series regression of the GMP growth rate against the U.S. GDP growth rate, and then obtain the intercept term, which essentially measures the temporal average, and the coefficient of the U.S. GDP growth rate, which measures the sensitivity of local GMP growth rate to the U.S. GDP growth rate, to measure local economy.

We obtain the data on local economic conditions from the websites of Bureau of Labor Statistics (BLS) and Bureau of Economic Analysis (BEA). BLE provides monthly total nonfarm employees and unemployment rate from January 2001 to November 2011 at the MSA and the national level. After retrieving the data, we first match the CBSAs for which the average systematic risk is estimated in this paper with the MSAs for which BLE provides the data on employees and unemployment rate using their names. Second, we calculate the monthly growth rate of the total nonfarm employees for each CBSA and at the national level. Third, we remove seasonality in the total nonfarm employee growth rate and the unemployment rates (see, e.g. Cleveland, Cleveland, McRae and Terpenning (1990)). Finally, for each CBSA, we regress the total nonfarm employee growth rate against the national employee growth rate, and obtain the intercept term and the coefficient to measure the temporal average growth and the sensitivity of CBSA employee growth to the national growth respectively. We run the same regression for each CBSA using the unemployment rates to obtain the temporal average and the CBSA sensitivity measurements for the unemployment rates.

BEA provides annual Gross Metropolitan Product for MSAs and the GDP for the U.S. from 2001 to 2010, as well as per capita GMP for MSAs and per capita GDP for the U.S over the same period. After retrieving the data, we also first match CBSAs in the NCREIF database with MSAs in the BEA database. We then calculate the annual growth rate in GMP/GDP and per capita GMP/per capita GDP, and remove their seasonality. Finally, we use the same regressions of

CBSA time series on the national time series to obtain the temporal average and the CBSA sensitivity of the GMP growth rate and per capita GMP growth rate for each CBSA we analyze.

Note that the measurements of local economic conditions constructed from BLS and BEA cover different sample periods than the systematic risk estimated from the NCREIF data. This might lead to biased estimation of the relationships between local economic conditions and the systematic risk if either the economic conditions or the systematic risk vary across time. This problem cannot be completely solved without a thorough analysis of the possible temporal variation in the systematic risk. However, this analysis is beyond the scope of this paper and is left for future research.

This paper hypothesizes that local supply elasticity of commercial real estate likely affects the systematic risk. However, we are unable to obtain reliable measurements for the supply elasticity. Therefore, we use the geographic measurement of the land supply constraints provided by Saiz (2010) as a proxy for the supply elasticity of commercial real estate. Note that this proxy has advantages and weaknesses. An important advantage is that it is likely exogenous for the real estate market as the geographic conditions are not caused by market conditions. An obvious weakness of this proxy is that it does not provide a comprehensive measurement for the supply elasticity as it does not contain information related to regulations and government controls, al of which affect the supply of space. Therefore, this proxy contains errors, which may lead to the attenuation effect that biases the coefficient estimates toward 0.

IV. Results

IV.1. Geographical distribution of the systematic risk

Tables 2 to 5 report the systematic risk of CBSAs that have at least 10 observations of property investments for the four property types respectively. Each table reports four numbers for each

CBSA: the number of property investments in this CBSA, the estimated systematic risk τ, the heteroskedastic-robust standard deviation of τ, and the t-statistic for the null hypothesis that $\tau = 1$ constructed using the heteroskedastic-robust standard deviation.

Table 2 reports the geographical distribution of the systematic risk for apartment properties, and provides two main results. First, there is strong evidence of the heterogeneity in the systematic risk across CBSAs. The risk measurement τ varies from 0.63 for Charlotte, NC, to 1.41 for New York, NY. Second, all the systematic risk that is lower than 0.9 and higher than 1.06 is statistically significantly different from 1. This includes the risk for CBSAs with very small number of investment observations, including Charlotte, NC, Kansas City, MO, Lake County, IL, and Tucson, AZ, all of which has only 10 observations. The strong results for these CBSAs seem to indicate that the GRSR is powerful in estimating the systematic risk for very thin markets.

Table 3 reports the results for industrial properties, which also substantiate the heterogeneity in the systematic across CBSAs. First, the systematic risk τ ranges from 0.41 for Memphis, TN, to 1.73 for Fort Worth, TX. Second, almost all the systematic risk that is lower than 1 and higher than 1.09 is statistically significantly different from 1, with Miami, FL, being the only exception. Similar to Table 1, Table 2 also indicates that the small numbers of observations do not prevent the GRSR from generating statistically significant estimates of the systematic risk. In fact, the two CBSAs that have only 10 observations, Columbus, OH, and Sacramento, CA, both have systematic risk that significantly differs from 1, which is 0.93 and 1.43 respectively.

Table 4 reports the systematic risk for office properties. In addition to the two results in Tables 2 and 3, which are strong evidence for heterogeneity in the systematic risk across CBSAs and the fact that the GRSR is powerful in thin markets, this table indicates that the range of the systematic risk in office property investments is wider than those of the apartment and industrial properties. Specifically, the systematic risk for office properties varies from 0.41 for West Palm Beach, FL, to 3.06 for New York, NY. This result appears to indicate that the geographical composition of properties may have a greater impact on the systematic risk of the portfolio for office properties than for apartment and industrial properties.

The results for retail properties are in Table 5. It is apparent that there are much fewer CBSAs, 13 to be specific, that have at least 10 observations of retail property investments. Nonetheless, the geographical distribution of the systematic risk is ostensible. Denver, CO, has the lowest systematic risk at 0.45, and Atlanta, GA, has the highest risk at 1.18.

IV.2. Determinants of CBSA level systematic risk

To analyze the determinants of CBSA level systematic risk of commercial real estate investments, particularly the possible relationships between the systematic risk and local economic conditions and land supply elasticity, we run cross-sectional regressions of CBSA systematic risk τ against a variety of measurements of local economic conditions, the land supply constraint measurement proposed by Saiz (2010), and the interaction terms between them. While we analyze a large variety of measurements of local economic conditions, including the GMP growth rate, the per capita GMP growth rate, the growth rate of total nonfarm employees, and the unemployment rate, we find no evidence for the impact of local economic conditions on the systematic risk at the CBSA level, with the only exception being that the land supply constraint seems to affect the systematic risk of apartment property investments.

Table 6 reports four specifications of the regression of apartment systematic risk on the land supply constraint and other variables, and shows some evidence that the land supply constraint may mitigate the risk. However, there is no evidence for the other three property types. The lack of relationship between local economic conditions and the systematic risk in commercial real estate investments is puzzling as property values are expected to be determined by the demand and supply for space, which is likely affected by local economic conditions and supply constraints. This puzzle calls for future research on the determinants of the risk in commercial real estate investments.

IV.3. Robustness check

The systematic risk reported in Tables 2 to 5 is measured as the sensitivity to in-sample estimates of market index returns. As discussed earlier, the in-sample estimates are not value-weighted averages of all properties in the U.S. market; therefore, the estimated systematic risk is not measured against the true national market. To investigate if the deviation of in-sample estimates of market indices from the true latent indices would bias the estimates of the systematic risk, we use alternative market indices to estimate the systematic risk as a robustness check. Specifically, we use the MIT transaction based indices (TBI), which is constructed using virtually all properties in the NCREIF database. For each property type, the systematic risk for each CBSA is estimated in (2) using the MIT TBIs as the market indices. Note that the MIT TBIs have covers a much shorter period than the in-sample estimates of market indices. Consequently, many investment observations in our data cannot be used to estimate CBSA systematic risk because there is no TBI value corresponding to their holding periods. This results in fewer CBSAs with the systematic risk estimated.

Figures 2 to 5 plots the systematic risk measured from in-sample estimates of market index returns against the risk estimated using the MIT TBIs for CBSAs for which both estimates are available. Figure 2 plots the systematic risk for apartment properties. Two results emerge. First, it is clear that the two estimates are highly correlated. For example, Charlotte, NC, has the lowest systematic risk, and San Diego, CA, has one of the highest risk values according to both measurements. Second, the magnitude of the two risk measurements is different. The risk estimated from in-sample estimates of market indices tend to be greater than the risk estimated using MIT TBIs. For instance, the systematic risk for Charlotte, NC, is 0.63 when estimated using the in-sample estimates of market index, but is about 0.4 when estimated using the MIT TBI index. These two results indicate that the GRSR provides robust results in ranking CBSAs based on their average systematic risk of commercial real estate investments, but the absolute level of the risk is sensitive to the measurement of the market index.

Figure 3, 4, and 5 plot the two systematic risk measurements for industrial, office, and retail properties. The two results discussed above, which are that the two risk measurements are correlated but the absolute levels differ, seem generally true for all these three property types, but the correlation between the two risk measurements seems the strongest for office properties. It is worth noting that, for retail, there are only three CBSAs that have both risk measurements. Nonetheless, the two risk measurements are highly correlated for them.

V. Conclusion

This paper is the first that analyzes the geographical distribution of the systematic risk in commercial real estate investments at the CBSA level. Using 3,240 institutional grade properties with detailed cash flow and location information from the NCREIF database, and overcoming the thin market problem with the Generalized Repeat Sales Regression, this paper finds two novel results. First, the systematic risk varies dramatically across CBSAs for each of four major property types: apartment, industrial, office and retail properties. Second, there is no evidence for any correlations between the CBSA systematic risk and local economic conditions or land supply constraints. These results have important implications for the assessment and management of the risk in real estate portfolios or mixed-asset portfolios that include direct real estate investments.

References

Brueggeman, W. B., A. H. Chen, and T. G. Thihodeau, 1984, Real estate investment funds: Performance and portfolio considerations, *Real Estate Economics* 12, 333-354.

Cleveland, R. B., W. S. Cleveland, J.E. McRae, and I. Terpenning, 1990, Stl: A seasonal-trend decomposition procedure based on loess, *Journal of Official Statistics* 6, 3-73.

Fisher, Jeffrey, and William Goetzmann, 2005, The performance of real estate portfolios: A simulation approach, *Journal of Portfolio Management* 32-45.

Geltner, David, 1989, Estimating real estate's systematic risk from aggregate level appraisal-based returns, *AREUEA Journal* 17, 463-481.

Goetzmann, William N., and Roger G. Ibbotson, 1990, The performance of real estate as an asset class, *Journal of Applied Corporate Finance* 3, 65-76.

Gordon, Myron J., 1962, The investment, financing, and valuation of the corporation, *Homewood, Illinois: Richard D. Irwin, Inc.*

Gyourko, Joseph, and Peter Linneman, 1988, Owner-occupied homes, income producing properties, and reits as inflation hedges: Empirical findings, *Journal of Real Estate Finance and Economics* 1, 347-372.

Hartzell, David J., John S. Hekman, and Mike E. Miles, 1986, Diversification categories in investment real estate, *Real Estate Economics* 14, 230-254.

Ling, David, and Andy Naranjo, 1997, Economic risk factors and commercial real estate returns, *Journal of Real Estate Finance and Economics* 14, 283-307.

Peng, Liang, 2010, Risk and returns of commercial real estate: A property level analysis, *Available at SSRN:* http://ssrn.com/abstract=1658265.

Peng, Liang, 2011, Repeat sales regression on heterogeneous properties, *Journal of Real Estate Finance and Economics* forthcoming.

Peng, Liang, and Thomas Thibodeau, 2012, Risk segmentation of american homes: Evidence from denver, *University of Colorado at Boulder working paper*.

Pivo, Gary, and Jeffrey D. Fisher, 2011, The walkability premium in commercial real estate investments, *Real Estate Economics* 39.

Plazzi, Alberto, Walter Torous, and Rossen Valkanov, 2008, The cross-sectional dispersion of commercial real estate returns and rent growth: Time variation and economic flucuations, *Real Estate Economics* 36, 403-439.

Saiz, Albert, 2010, The geographic determinants of housing supply, *Quarterly Journal of Economics* 125, 1253-1296.

Table 1 Summary of Sample Properties

This table reports the number of properties in the sample and the mean and the standard deviation of the following variables for each property type: the gross square feet, the purchase price, the net sale proceeds, the purchase cap rate (the annual NOI after the purchase divided with the purchase price), the going-out cap rate (the annual NOI before the disposition divided with the net sale proceeds), the holding period (the number of quarters from the acquisition to the disposition).

	Apartment	Industrial	Office	Retail
Properties	911	898	1,012	419
Gross Square Feet Mean	288,071	333,187	240,098	223,664
Gross Square Feet Std. Dev.	160,288	414,858	266,088	230,105
Purchase Price Mean	$23,823,798	$14,867,896	$36,560,020	$24,695,338
Purchase Price Std. Dev.	$15,671,753	$17,515,553	$56,970,313	$27,817,381
Net Sale Proceeds Mean	$30,459,085	$17,612,355	$45,716,430	$29,963,181
Net Sale Proceeds Std. Dev.	$23,153,760	$22,134,178	$79,713,453	$35,025,231
Purchase Cap Rate Mean	7.14%	8.53%	8.49%	8.69%
Purchase Cap Rate Std. Dev.	2.26%	2.63%	2.92%	2.56%
Going-out Cap Rate Mean	6.50%	7.43%	7.40%	7.79%
Going-out Cap Rate Std. Dev.	2.07%	2.74%	2.89%	2.32%
Annualized IRR Mean	8.26%	6.61%	7.43%	10.10%
Annualized IRR Std. Dev.	12.01%	14.53%	12.86%	12.59%
Holding Period Mean	18	15	18	18
Holding Period Std. Dev.	10	10	11	11

Table 2 Geography of Systematic Risk: Apartment

This table reports the number of observations of apartment investments (Properties), the systematic risk (Tao), the heteroskedasticity-robust standard deviation of the systematic risk (Stand. Dev.), and the t-statistic from testing the null hypothesis that the systematic risk equals 1 for 34 CBSAs that have 10 or more observations of apartment property investments.

CBSA	Properties	Tao	Stand. Dev.	T-statistic
NC - Charlotte	10	0.63	0.04	-9.15
NC - Raleigh	17	0.68	0.01	-54.04
MO - Kansas City	10	0.72	0.02	-15.14
TX - Dallas	53	0.75	0.00	-81.70
MD - Baltimore	17	0.77	0.04	-5.63
OR - Portland	19	0.81	0.01	-13.62
TX - San Antonio	12	0.81	0.02	-10.97
FL - Orlando	21	0.83	0.01	-23.80
FL - Miami	13	0.84	0.03	-6.29
GA - Atlanta	64	0.85	0.02	-8.09
IL - Lake County	10	0.88	0.03	-4.06
TX - Austin	29	0.89	0.01	-16.14
PA - Philadelphia	10	0.89	0.05	-2.03
NV - Lad Vegas	13	0.89	0.02	-6.72
TX - Fort Worth	16	0.90	0.01	-9.54
MD - Bethesda	11	0.93	0.08	-0.87
FL - Tampa	20	0.99	0.02	-0.37
IN - Indianapolis	15	1.02	0.01	1.64
WA - Seattle	25	1.02	0.01	1.90
IL - Chicago	20	1.04	0.02	1.63
CA - Santa Ana	12	1.05	0.13	0.43
CO - Denver	20	1.06	0.00	26.04
TN - Nashville	12	1.07	0.03	2.39
DC - Washington	26	1.08	0.01	8.48
AZ - Tucson	10	1.09	0.15	6.38
MN - Minneapolis	13	1.13	0.02	5.54
FL - Fort Lauderdale	36	1.17	0.02	11.04
AZ - Phoenix	41	1.18	0.01	29.11
FL - West Palm Beach	21	1.23	0.03	7.71
TX - Houston	38	1.27	0.03	9.25
CA - Los Angeles	27	1.33	0.03	10.58
CA - Riverside	24	1.35	0.01	34.62
CA - San Diego	19	1.36	0.05	7.69
NY - New York	14	1.41	0.04	9.86

Table 3 Geography of Systematic Risk: Industrial

This table reports the number of observations of industrial property investments (Properties), the systematic risk (Tao), the heteroskedasticity-robust standard deviation of the systematic risk (Stand. Dev.), and the t-statistic from testing the null hypothesis that the systematic risk equals 1 for 28 CBSAs that have 10 or more observations of industrial property investments.

CBSA	Properties	Tao	Stand. Dev.	T-statistic
TN - Memphis	15	0.41	0.11	-5.61
NJ - Edison	14	0.47	0.09	-5.83
TX - Dallas	61	0.57	0.01	-33.88
CO - Denver	14	0.72	0.09	-3.05
FL - Fort Lauderdale	12	0.73	0.09	-3.12
WA - Seattle	29	0.76	0.06	-3.87
TX - Houston	25	0.88	0.01	-12.49
OH - Columbus	10	0.93	0.03	-2.79
MA - Cambridge	11	1.03	0.02	1.96
CA - San Francisco	12	1.05	0.18	0.29
CA - San Diego	28	1.08	0.05	1.65
CA - Oakland	34	1.09	0.02	3.86
FL - Orlando	12	1.10	0.03	3.33
MA - Boston	11	1.11	0.02	5.26
FL - Miami	11	1.12	0.08	1.45
AZ - Phoenix	39	1.15	0.03	4.75
CA - San Jose	24	1.16	0.01	11.61
IL - Chicago	55	1.17	0.04	4.10
MN - Minneapolis	12	1.25	0.11	2.26
MD - Baltimore	26	1.28	0.02	13.58
GA - Atlanta	74	1.29	0.02	15.31
CA - Santa Ana	48	1.30	0.01	36.35
NC - Charlotte	12	1.32	0.04	8.05
CA - Los Angeles	73	1.36	0.01	36.97
CA - Riverside	29	1.42	0.04	9.46
CA - Sacramento	10	1.43	0.02	27.39
DC - Washington	16	1.70	0.08	9.02
TX - Fort Worth	16	1.73	0.04	20.58

Table 4 Geography of Systematic Risk: Office

This table reports the number of observations of office investments (Properties), the systematic risk (Tao), the heteroskedasticity-robust standard deviation of the systematic risk (Stand. Dev.), and the t-statistic from testing the null hypothesis that the systematic risk equals 1 for 29 CBSAs that have 10 or more observations of office property investments.

CBSA	Properties	Tao	Stand. Dev.	T-statistic
FL - West Palm Beach	12	0.41	0.19	-3.16
GA - Atlanta	56	0.55	0.03	-13.57
CO - Denver	25	0.59	0.02	-20.02
MN - Minneapolis	23	0.60	0.07	-6.07
CA - Oakland	18	0.88	0.11	-1.08
IL - Chicago	64	0.97	0.04	0.91
MO - Kansas City	11	0.99	0.04	-0.27
TX - Dallas	40	1.15	0.07	2.10
CA - San Jose	14	1.15	0.25	0.60
CA - Los Angeles	66	1.20	0.05	4.13
FL - Orland	14	1.22	0.03	6.55
CA - San Francisco	23	1.25	0.04	5.62
AZ - Phoenix	35	1.28	0.09	3.13
NC - Raleigh	12	1.28	0.16	1.77
TX - Houston	44	1.33	0.02	13.38
FL - Tampa	13	1.34	0.12	2.94
MA - Cambridge	23	1.47	0.03	16.76
TX - Austin	13	1.46	0.04	11.72
MO - St. Louis	15	1.50	0.04	12.14
FL - Miami	10	1.53	0.16	3.32
MD - Bethesda	16	1.54	0.03	21.47
OR - Portland	16	1.56	0.05	10.33
CA - San Diego	47	1.56	0.04	13.16
DC - Washington	97	1.59	0.01	56.77
PA - Philadelphia	13	1.79	0.04	18.57
MA - Boston	22	1.91	0.09	10.43
CA - Santa Ana	27	1.94	0.04	25.12
WA - Seattle	20	2.03	0.06	18.06
NY - New York	32	3.06	0.14	15.25

Table 5 Geography of Systematic Risk: Retail

This table reports the number of observations of retail property investments (Properties), the systematic risk (Tao), the heteroskedasticity-robust standard deviation of the systematic risk (Stand. Dev.), and the t-statistic from testing the null hypothesis that the systematic risk equals 1 for 13 CBSAs that have 10 or more observations of retail property investments.

CBSA	Properties	Tao	Stand. Dev.	T-statistic
CO - Denver	13	0.45	0.00	-885.33
CA - San Diego	12	0.52	0.01	-54.46
WA - Seattle	13	0.61	0.02	-16.79
CA - Oakland	10	0.71	0.01	-47.66
TX - Dallas	10	0.72	0.02	-14.71
MN - Minneapolis	13	0.80	0.01	-25.49
AZ - Phoenix	14	0.81	0.02	-12.38
IL - Chicago	20	0.83	0.01	-20.78
FL - Orlando	12	0.94	0.02	-2.83
FL - West Palm Beach	11	0.94	0.01	-6.35
PA - Philadelphia	10	0.98	0.01	-2.31
DC - Washington	31	1.03	0.00	9.25
GA - Atlanta	13	1.18	0.01	23.55

Table 6 CRE Systematic Risk and Economic Systematic Risk: Apartment

This table reports results of cross-sectional regressions of CBSA systematic risk in apartment property investments against local economic conditions and land supply constraints. Explanatory variables for each CBSA include the land supply constraint (Constraint) measured by Saiz (2010), the temporal average of the Gross Metropolitan Product growth rate (GMP alpha) and the sensitivity of the GMP growth rate to the U.S. GDP growth rate (GMP beta), which are respectively the intercept term and the coefficient from a time series regression of CBSA GMP growth rates against the U.S. GDP growth rates, the temporal average of the unemployment rate rate (Unemployment alpha) and the sensitivity of the CBSA unemployment rate to the U.S. unemployment rate (Unemployment beta), which are respectively the intercept term and the coefficient from a time series regression of CBSA unemployment rates against the U.S. unemployment rates, and interactions between the GMP and unemployment variables and Constraint. Heteroskedasticity-robust standard deviations are in parentheses. *** denotes significance at the 1% level, ** at the 5% level, and * at 10% level.

	I	II	III	IV
Intercept term	1.20***	1.36***	1.19***	1.06***
	(0.10)	(0.16)	(0.12)	(0.34)
Constraint	-0.11**	-0.16**	-0.11*	-0.01
	(0.05)	(0.08)	(0.06)	(0.16)
GMP alpha	2.22			
	(7.59)			
GMP alpha*Constraint	-0.50			
	(2.91)			
GMP beta		-0.17		
		(0.10)		
GMP beta*Constraint		0.06		
		(0.04)		
Unemployment alpha			-0.00	
			(0.05)	
Unemployment alpha*Constraint			0.01	
			(0.03)	
Unemployment beta				0.12
				(0.28)
Unemployment beta*Constraint				-0.11
				(0.15)
Sample size	29	29	29	29
Adjusted R2	0.14	0.24	0.13	0.16

Figure 1

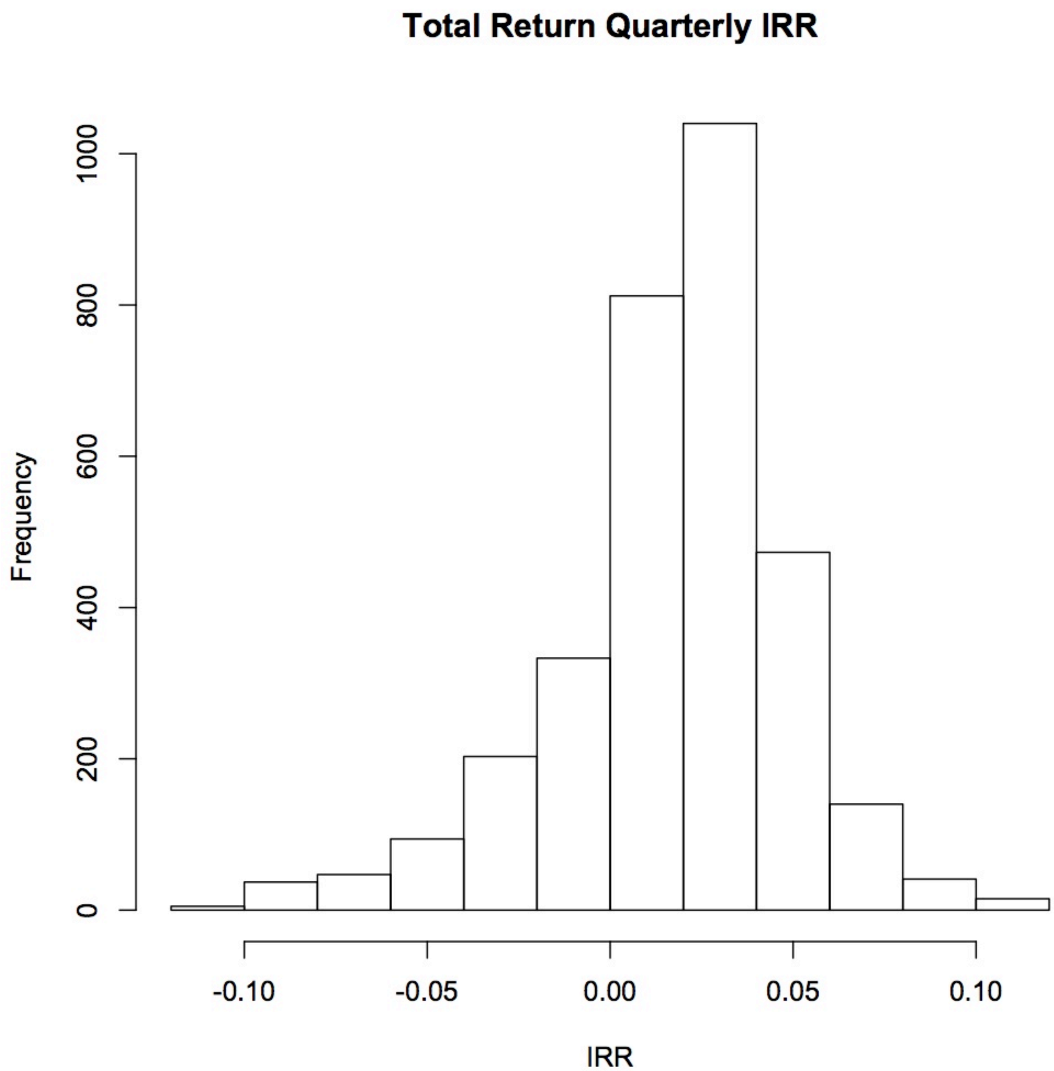

Total Return Quarterly IRR
Frequency
0
200
400
600
800
1000
-0.10
-0.05
0.00
0.05
0.10
IRR

Figure 2

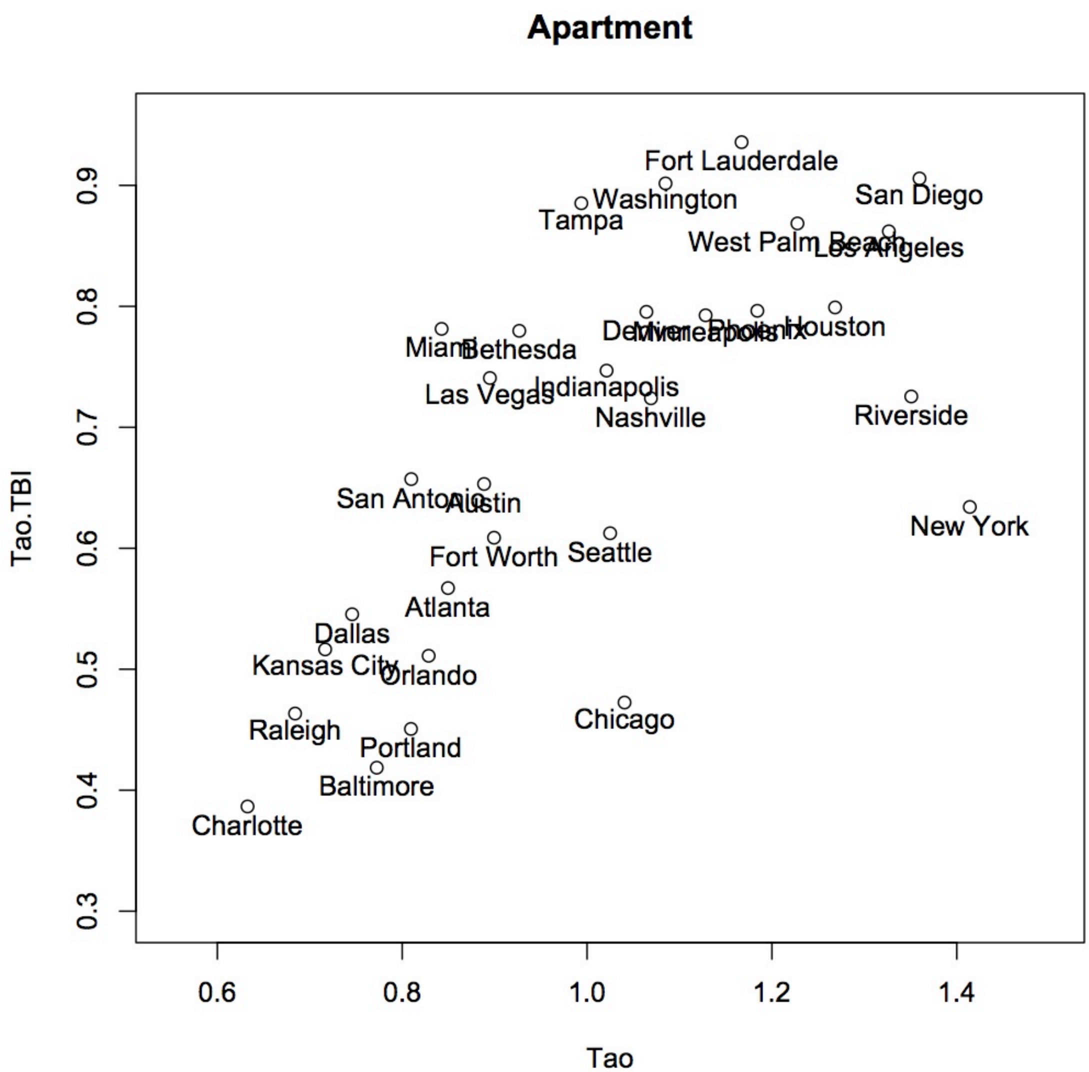

Apartment
Tao.TBI
Tao
0.3
0.4
0.5
0.6
0.7
0.8
0.9
0.6
0.8
1.0
1.2
1.4
Fort Lauderdale
Washington
San Diego
Tampa
Houston
Miami
Bethesda
Indianapolis
Las Vegas
Nashville
Riverside
San Antonio
Austin
New York
Fort Worth
Seattle
Atlanta
Dallas
Kansas City
Orlando
Chicago
Raleigh
Portland
Baltimore
Charlotte

Figure 3

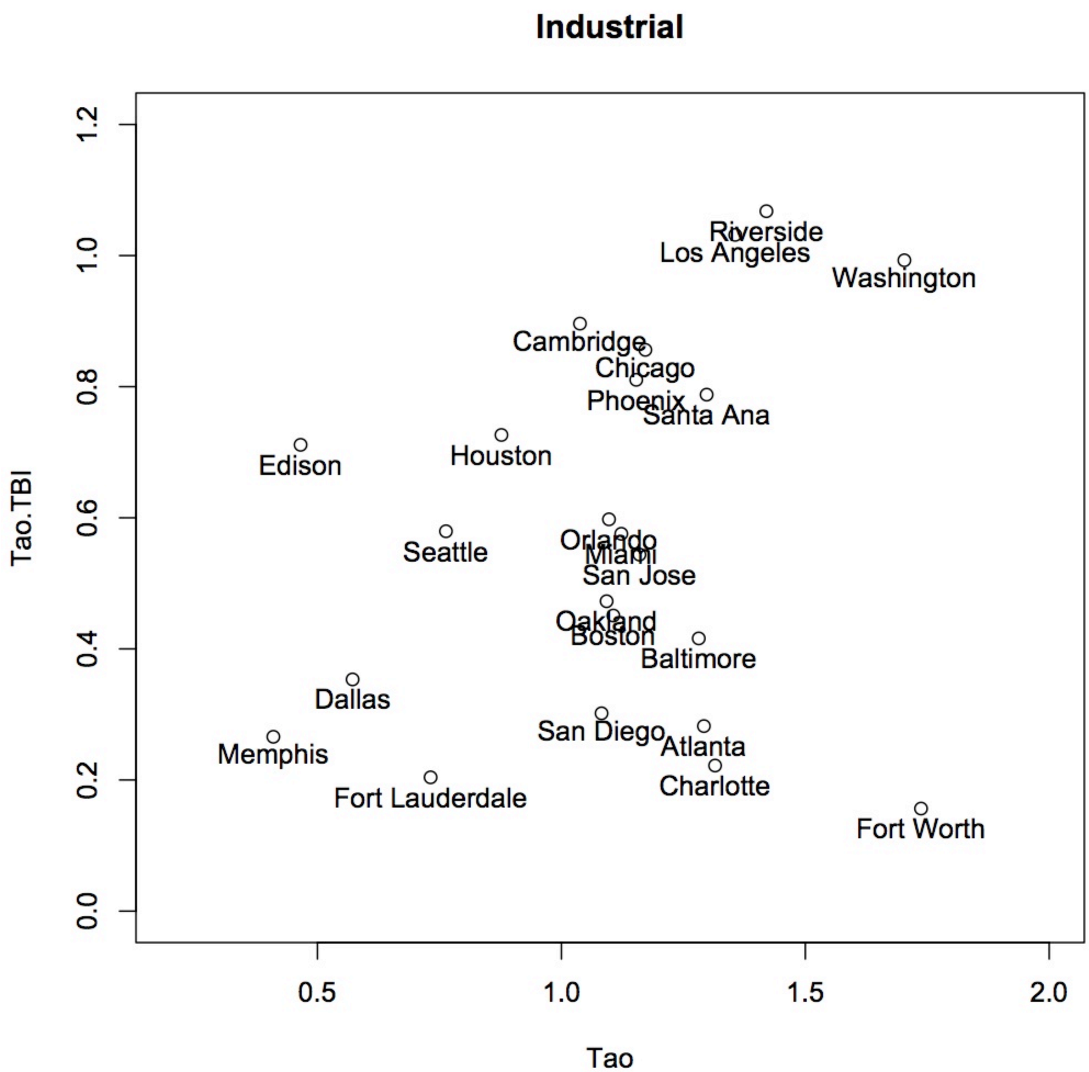
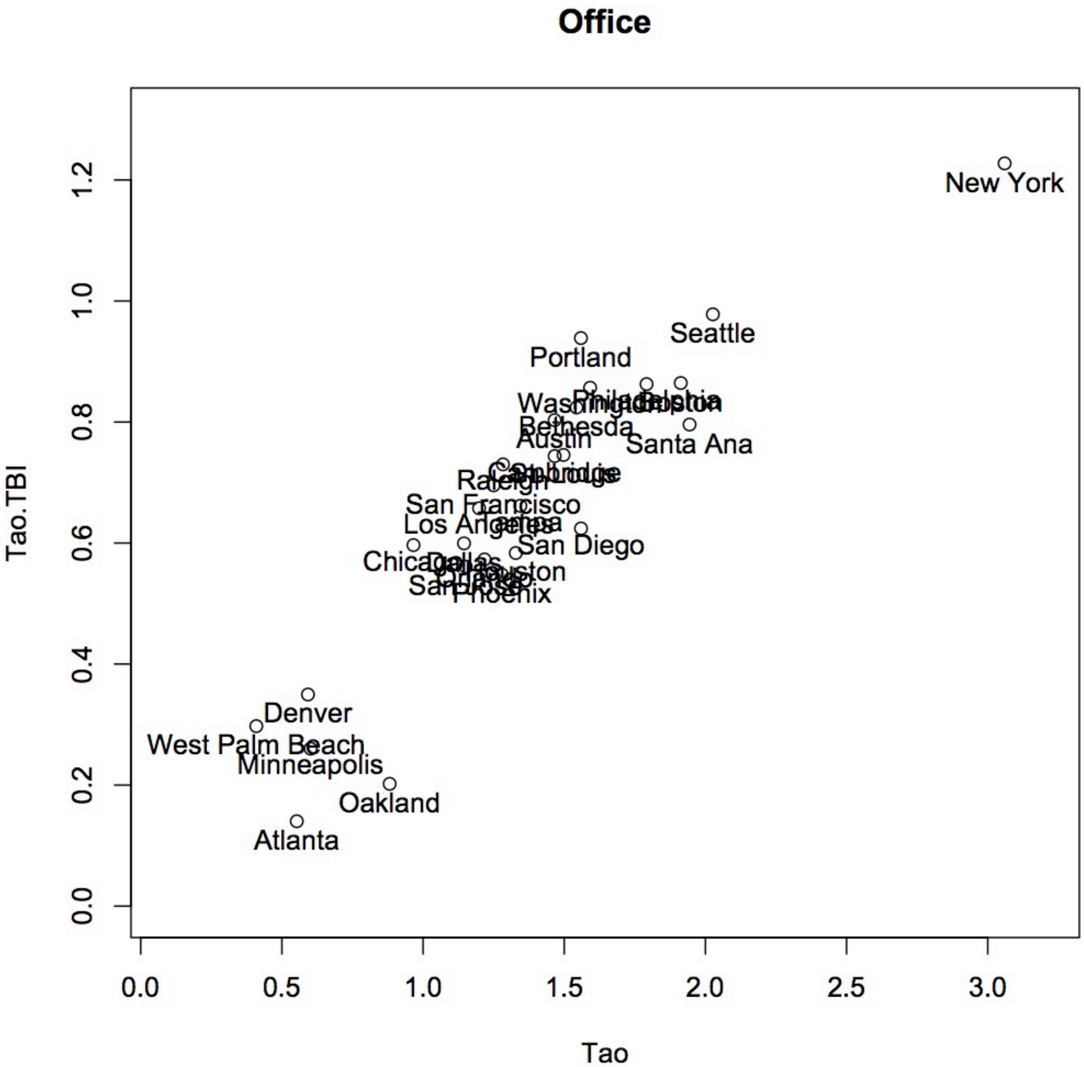
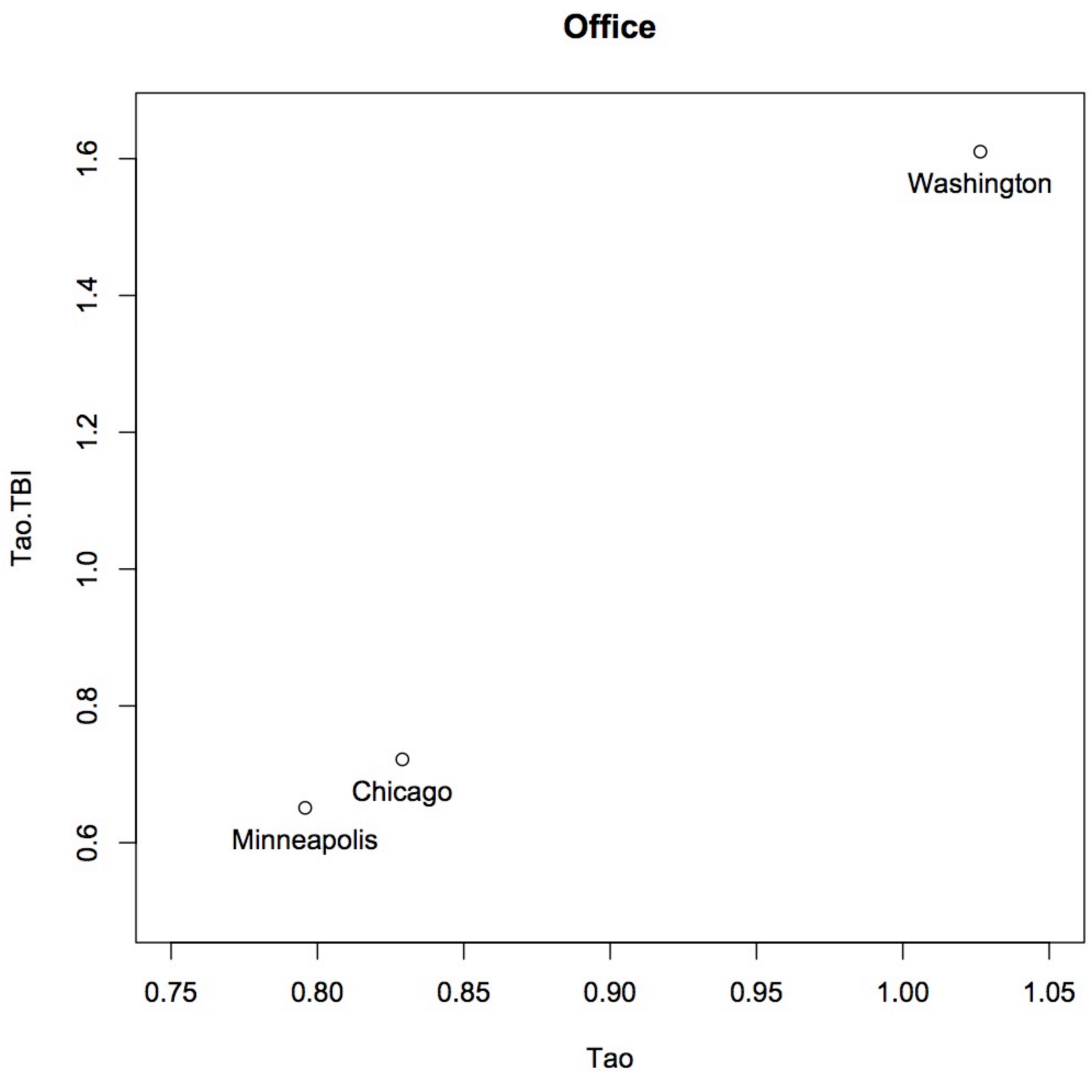

Industrial
Tao.TBI
Tao
0.0
0.2
0.4
0.6
0.8
1.0
1.2
0.5
1.0
1.5
2.0
Riverside
Los Angeles
Washington
Cambridge
Chicago
Phoenix
Santa Ana
Edison
Houston
Seattle
Orlando
Miami
San Jose
Oakland
Boston
Baltimore
Dallas
Memphis
San Diego
Atlanta
Charlotte
Fort Lauderdale
Fort Worth

Figure 4



Office
New York
Seattle
Portland
Santa Ana
Bethesda
Austin
San Francisco
Los Angeles
San Diego
Phoenix
Denver
West Palm Beach
Minneapolis
Oakland
Atlanta
Tao.TBI
0.0
0.2
0.4
0.6
0.8
1.0
1.2
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Tao

Figure 5



Office
Washington
Chicago
Minneapolis
Tao.TBI
Tao
1.6
1.4
1.2
1.0
0.8
0.6
0.75
0.80
0.85
0.90
0.95
1.00
1.05