

Anderson Graduate School of Management

Finance

(University of California, Los Angeles)

Year 2004

Paper 13'04

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Alberto Plazzi
University of Verona

Walt Torous
UCLA

Rossen Valkanov
UCLA

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Expected Returns and the Expected Growth in Rents of Commercial Real Estate*

Alberto Plazzi
The Anderson School
UCLA[†]
and
University of Verona

Walter Torous
The Anderson School
UCLA[‡]

Rossen Valkanov
The Anderson School
UCLA[§]

This Draft: July 2004 ¶

*We thank Harrison Hong, Andrey Pavlov, and Antonio Rubia for comments.

[†]Los Angeles, CA 90095-1481, phone: (310) 206-9424, fax: (310) 206-5455, e-mail: alberto.plazzi@anderson.ucla.edu.

[‡]Los Angeles, CA 90095-1481, phone: (310) 825-4059, fax: (310) 206-5455, e-mail: walter.n.torous@anderson.ucla.edu.

[§]Corresponding author. Los Angeles, CA 90095-1481, phone: (310) 825-7246, fax: (310) 206-5455, e-mail: rossen.valkanov@anderson.ucla.edu.

¶The latest draft is available at: <http://www.personal.anderson.ucla.edu/rossen.valkanov/>.

Abstract

We investigate whether the cap rate, that is, the rent-price ratio in commercial real estate incorporates information about future expected real estate returns and future growth in rents. Relying on transactions data spanning several years across fifty-three metropolitan areas in the U.S., we find that the cap rate captures fluctuations in expected returns for apartments, retail, as well as industrial properties. For offices, by contrast, the cap rate does not forecast returns even though additional evidence reveals that expected returns on offices are also time-varying. We link the mixed success of the cap rate in forecasting commercial property returns to differences in the stochastic properties of their rental growth rates. In particular, the low correlation between the cap rate and future office returns is due to the growth in office rents having a higher correlation with expected returns and being more volatile than other property types. Taken together, the evidence suggests that variations in commercial real estate prices are largely due to movements in discount rates as opposed to cash flows.

1 Introduction

U.S. commercial real estate prices fluctuate considerably both cross-sectionally and over time. For example, the returns to apartments during the last quarter of 1994 ranged from 21.4 percent in Dallas, Texas to -8.5 percent in Portland, Oregon. Eight years later, during the last quarter of 2002, the returns to apartments in Dallas and Portland were 1.2 and 4.4 percent, respectively. Other types of commercial real estate, such as retail, industrial, and office properties, have experienced even larger return fluctuations. Understanding what drives these fluctuations is a challenging and important research question since commercial real estate represents a substantial fraction of total U.S. wealth. In particular, the total value of commercial real estate in the U.S. as of the end of 1999 was estimated to be approximately six trillion dollars, which at the time represented almost half of the value of the U.S. stock market (Case (2000)).

From an asset pricing perspective, the price of a commercial property, be it an office building, apartment building, retail or industrial space, should equal the present value of its future rents. This fundamental present value relation implies that the observed fluctuations in commercial real estate prices should reflect variations in future rents or future discount rates. In valuing commercial real estate, it is particularly important to consider the possibility that discount rates and growth in rents are time-varying as it is often conjectured that they fluctuate with the prevailing state of the economy. For example, Case (2000) points out “the vulnerability of commercial real estate values to changes in economic conditions” by describing recent boom-and-bust cycles in that market. He provides a simple illustration where cyclical fluctuations in expected returns and growth in rents result in sizable variations in commercial real estate prices. Case, Goetzmann, and Rouwenhorst (2000) make a similar point using international data and conclude that commercial real estate is “a bet on fundamental economic variables.” Despite these and other studies, little is known about the movement of commercial real estate prices.

In this paper, we investigate whether expected returns and the expected growth in rents of commercial real estate are time-varying using a version of Campbell and Shiller’s (1988) “dynamic Gordon” model. A direct implication of that model is that the cap rate, defined as the ratio between a property’s net rent (rent minus expenses adjusted for vacancies) and its price, should reflect fluctuations in expected returns or rental growth rates. The cap rate is a standard measure of commercial real estate valuation and corresponds to a common

stock's dividend-price ratio where the property's net rent plays the role of a dividend. As an illustration, suppose that the apartment cap rate in Portland is higher than the cap rate of similar apartments in Dallas. The dynamic Gordon model implies that either future discount rates in Portland will be higher than in Dallas or that future rents in Portland will grow at a slower rate than in Dallas. Whether or not cap rates actually forecast future returns or future rent growth depends on the variability of these processes, their persistence, and their mutual correlation and is ultimately an empirical question.

To investigate whether cap rates capture variations in future returns and rental growth rates to commercial real estate, we use a novel dataset of transactions data across fifty-three U.S. metropolitan areas over the sample period 1994 to 2003 at a quarterly frequency. For a subset of twenty-one of these regions, we also have bi-annual observations beginning in the last quarter of 1985. These data are available on a variety of property types including offices, apartments, as well as retail and industrial real estate. The transactions nature of our commercial real estate data differentiates it from the data typically relied upon in many other real estate studies including investigations of residential real estate. For example, we verify that returns and rental growth rates in our data are not serially correlated beyond a yearly horizon as are returns of residential properties and returns of real estate obtained from appraisals (Case and Shiller (1989,1990)).

Relying on these data, we find that higher cap rates predict higher future returns on apartment buildings as well as retail and industrial properties. However, cap rates cannot predict future returns to office buildings. For apartments, retail, and industrial buildings, the predictability of returns is robust to controlling for cross-sectional differences using fixed effects as well as variables that capture regional differences reflecting demographic, geographic, and economic factors. In terms of the economic significance of this predictability, we find that a one percent increase in cap rates leads to an increase of up to four percent in the prices of these properties. This large effect is due to the persistence of the fluctuations in expected returns and is similar in magnitude to that documented for stocks (Cochrane (2001)). By contrast, we do not find reliable evidence that cap rates predict future movements in rental growth rates. Only for offices do we find limited evidence of lower cap rates predicting higher future rental growth rates and then only at long horizons. However, this does not imply that the rental growth rates of commercial real estate are not time-varying. On the contrary, their variability is similar to, and in the case of offices even larger than, the volatility of the growth in the dividends of the stock market.

Our results point to a fundamental difference between apartments, retail properties, and industrial properties on the one hand, where cap rates forecast returns, and office buildings on the other, where cap rates do not. This then provides us with a unique opportunity to analyze the dynamic Gordon model and better understand under what conditions valuations ratios can or cannot predict future returns. From this model, it is well known that the cap rate will predict time-varying expected returns under two conditions. First, expected returns and expected rental growth rates must be uncorrelated. If they are correlated, then fluctuations in one series will offset, on average, fluctuations in the other and the cap rate will remain unchanged. Second, extreme movements in rental growth rates that are orthogonal to the time variation in expected returns will make it difficult to detect a statistically reliable forecasting relation. These assumptions have been discussed by Campbell and Shiller (1988b), Campbell, Lo, and MacKinlay (1997), and more recently by Lettau and Ludvigson (2004) and Menzly, Santos, and Veronesi (2004) but only in the context of stocks. Based on this discussion, there are two possible interpretations for the lack of forecastability by office cap rates. It may be the case that the expected returns of office buildings are much less time-varying than the expected returns of other commercial property types. Alternatively, cap rates may fail to forecast the variation in future office returns because office rental growth rates are more correlated with expected returns or are more volatile than the rental growth rates of other properties. These alternatives have very different implications for asset pricing and portfolio allocation.

We find that the future returns of all four commercial property types are similarly correlated with macroeconomic variables, such as the term spread, default spread, inflation, and the short interest rate. These variables are known to capture fluctuations in business cycle conditions and have been widely used in the stock return predictability literature to track the time-varying behavior in aggregate stock market returns (Campbell and Shiller (1988a), Campbell (1991), Fama and French (1989), Lettau and Ludvigson (2004), Torous, Valkanov, and Yan (2005) and, for a good review, Campbell, Lo, and MacKinlay (1997)). Furthermore, we find not only that the rent growth rates of all four commercial property types are correlated with these macroeconomic variables but also that for offices, the correlation is significantly larger. We also show that the volatility in rent growth that is orthogonal to the macroeconomic variables is much higher for offices than for the other property types and is even slightly higher than the volatility of the stock market's dividend growth rate over our sample period, 8.5 percent versus 8.1 percent. Hence, we conclude that while expected returns of offices are time-varying, the failure of cap rates to forecast their future variation

reflects the fact that the growth in office rents is also correlated with the state of the economy while the orthogonal remainder is also very volatile.

The view of commercial real estate that emerges from this paper is that of an asset class that is characterized by fluctuations in expected returns not unlike that of common stock. All property types including offices exhibit time-varying returns which are forecastable using precisely the same business cycle proxies that have been found to forecast common stock returns. Even though expected rental growth rates of apartments, retail, and industrial commercial real estate are not related to business cycle variables, our results suggest that portfolio managers should think twice if they expect investment in commercial real estate to hedge the cyclical variation of common stock. Office properties provide the worst hedge as their rental growth rates do vary with the state of the economy.

Commercial real estate, however, differs from stocks in several important aspects. For example, it is often argued that common stock dividends may not accurately reflect changing investment opportunities confronting a firm. Dividends are paid at the discretion of the firm's management and there is ample evidence that they are either actively smoothed, the product of managers catering to investors' demand for dividends, or the result of managers' reaction to perceived mispricings (Shefrin and Statman (1984), Stein (1996), and Baker and Wurgler (2004)). Dividends are also subject to long term trends such as the recent decrease in the propensity of firms to pay dividends (Fama and French (2001)). By contrast, rents on commercial properties are not discretionary and are paid by tenants as opposed to property managers. Furthermore, rents are not fixed but rather are sensitive to prevailing business conditions. Another difference is that commercial real estate is not publicly traded and is characterized by higher transactions costs. Hence, our analysis focuses on long horizon (one to five years) predictability, where these factors are likely to be less important. Finally, the prices of commercial properties are likely to be more sensitive than stocks to geographic, demographic, and local economic factors. To capture these sensitivities, following Abraham and Hendershott (1996), Capozza, Hendershott, Mack, and Mayer (2002), and Glaeser, Gyourko, and Saks (2004), for each metropolitan area we use population growth, per capita income growth, employment growth, the growth in construction costs, coastal region dummies, as well as several other urbanization proxies to control for these cross-sectional differences.

The plan of this paper is as follows. In Section 2, we present the valuation framework and discuss its application to commercial real estate taking special care to account for

regional differences as well as differences across property types. In Section 3, we discuss the new commercial real estate data. The main predictive results are presented in Section 4 along with various robustness checks. The economic significance of the predictability and its implication for volatility in commercial real estate prices is discussed in Section 5. In Section 6, we provide further evidence on the time variability of expected returns in commercial real estate. We link the differences in predictability results across property types to differences in forecastability and to differences in variability of their rental growth rates. In Section 7, we offer concluding remarks.

2 Real Estate Returns, Rents, and Growth in Rents

2.1 The Rent-Price Ratio Model

We denote by P_t the price of, say, an apartment at the end of period t and by H_{t+1} its net rental value (rent minus operating expenses, adjusting for vacancies) from period t to $t + 1$. The gross return from holding the apartment from t to $t + 1$ is:

$$1 + R_{t+1} \equiv \frac{P_{t+1} + H_{t+1}}{P_t}. \quad (1)$$

The above definition of the return to real estate is similar to that of a stock return. The only difference is that a commercial property provides real estate services at a market value H_{t+1} instead of dividends.

If we define the log return as $r_{t+1} \equiv \log(1 + R_{t+1})$ and the log net rent as $h_{t+1} \equiv \log(H_{t+1})$, we can follow Campbell and Shiller (1988) and express r_{t+1} using a first-order Taylor approximation as $r_{t+1} \approx \kappa + \rho p_{t+1} + (1 - \rho)h_{t+1} - p_t$, where κ and ρ are two parameters derived from the linearization.¹ We solve this relation forward, impose the transversality condition $\lim_{k \rightarrow \infty} \rho^k p_{t+k} = 0$ that avoids the presence of rational bubbles, take expectations at time t , and obtain the following present-value relation for the log price $p_t \equiv \log(P_t)$ of a

¹In particular, $\rho \equiv 1/(1 + \exp(\overline{h - p}))$, being $\overline{h - p}$ the average log rent - price ratio; note that for the US real estate market, the average log rent - price ratio in the period 1994 - 2003 has been about 8.5% annually, implying a value for ρ of 0.92 in annual terms, that is slightly lower than the 0.97 in the equity market for the same period.

real estate property:

$$p_t = \frac{\kappa}{1 - \rho} + E_t \left[\sum_{k=0}^{\infty} \rho^k [(1 - \rho)h_{t+1+k} - r_{t+1+k}] \right]. \quad (2)$$

Expression (2) states that a high property price today reflects the expectation of high future rents or lower future expected returns or both. If real estate markets are efficient, then information about future cash flows or future discount rates is immediately reflected in property prices. Expression (2) has been previously used in the asset pricing literature to analyze the fluctuations of equity returns (see Campbell and Shiller (1988b) and Campbell (2003) for a review).

If the growth in rents and expected return are both stationary, expression (2) implies a log-linear approximation of the rent-price ratio which will facilitate our subsequent empirical analysis. In the real estate literature, the (net) rent-price ratio H_t/P_t is often referred to as the cap rate (Geltner and Miller (2000)). Therefore, if we define $cap_t \equiv h_t - p_t$, from expression (2) we can write:

$$cap_t = -\frac{\kappa}{1 - \rho} + E_t \left[\sum_{k=0}^{\infty} \rho^k r_{t+1+k} \right] - E_t \left[\sum_{k=0}^{\infty} \rho^k \Delta h_{t+1+k} \right]. \quad (3)$$

The above equation is best understood as a consistency relation. It states that if the cap rate of a property is high, then either the property's expected return is high, or the expected growth in its rents is low, or both. This log-linearization framework was proposed by Campbell and Shiller (1988b) as a generalization of Gordon's (1962) constant-growth model and allows expected returns and dividend growth rates to be time-varying. Like any other financial asset, there are good reasons to believe that expected returns to commercial real estate and rent growth rates are time-varying. We will use expression (3) as the starting point for our analysis of pricing fluctuations of commercial real estate properties.

To proceed, we must make additional assumptions about the dynamics of expected returns, $E_t r_{t+1}$, as well as expected rental growth rates, $E_t \Delta h_{t+1}$. Suppose that expected returns follow an autoregressive process of order one ($AR(1)$) with coefficient $|\phi| < 1$:

$$E_t r_{t+1} = r + x_t = r + \phi x_{t-1} + \xi_t \quad (4)$$

where r and $r + x_t$ are the unconditional and conditional expected returns at time t , respectively. The vector x_t contains a set of conditioning information such as the term spread, the default spread, inflation, or the short interest rate which have been previously shown to capture time-varying economic conditions (Campbell (1991), Campbell and Shiller (1988a), Chen, Roll, and Ross (1986), Fama (1990), Fama and French (1988, 1989), Ferson and Harvey (1991), and Keim and Stambaugh (1986), among others), and ξ_t is a white noise disturbance. The $AR(1)$ process provides a parsimonious representation of slowly evolving economic conditions.

We further assume that the expected growth of rents is also time-varying,

$$\begin{aligned} E_t \Delta h_{t+1} &= g + \tau x_t + y_t \\ &= g + \tau x_t + \psi y_{t-1} + \zeta_t \end{aligned} \tag{5}$$

where g is the unconditional expected rental growth rate and ζ_t is a white noise disturbance. A non-zero value of τ implies that rent growth and expected returns are correlated. If $\tau = 1$ then both rent growth and expected returns respond equivalently to changing economic conditions. The y_t term represents the variation in the rent growth that is orthogonal to the variation in expected returns. We allow y_t to also be serially correlated. Lettau and Ludvigson (2004) use a similar setup to model the correlation between expected returns and expected dividend growth in stocks.

Using expressions (4) and (5), the cap rate from expression (3) can be written as (ignoring the κ terms):

$$cap_t = \frac{r - g}{1 - \rho} + \left[\frac{x_t(1 - \tau)}{1 - \rho\phi} - \frac{y_t}{1 - \rho\psi} \right]. \tag{6}$$

The first term in expression (6) reflects the difference between the unconditional expected return and the unconditional rent growth.² In the second term, the rent-price ratio captures time-varying fluctuations in expected returns and growth in rents. Larger deviations from unconditional expected returns (large x_t) or more persistent deviations (large ϕ) imply higher cap rates. Fluctuations in expected rent growth that are orthogonal to expected returns (y_t) are negatively correlated with the cap rate.

We can immediately see that if expected returns and expected rent growth rates are

²This difference is assumed to be positive following the intuition behind the Gordon model.

correlated, that is, τ is between zero and one, then it will be difficult for the cap rate to forecast expected returns. In the extreme case where expected rent growth rates move one for one with expected returns, $\tau = 1$, the cap rate will be unable to detect fluctuations in expected returns because the variation in expected returns will be precisely offset by corresponding fluctuations in expected rent growth. Detecting a forecasting relation between the cap rate and expected returns is also made difficult if the variation in the rent growth rate is large.

Expressions (3) and (6) impose testable restrictions on the time series behavior of asset prices. The existing literature (see, e.g., Campbell and Shiller (1988b), Fama and French (1988), Campbell, Lo, and MacKinlay (1997), Lettau and Ludvigson (2004)) tests this relation for the US stock market and the main findings can be summarized as follows: (i) the dividend-price ratio is somewhat successful at capturing movements in future expected stock returns; (ii) the dividend-price ratio is a “smooth” variable and captures movements in expected returns at longer horizons; and (iii) the dividend-price ratio does not seem to capture fluctuations in dividend growth rates which appear to be close to *i.i.d.*³ The stock market time series regressions require a lengthy series of data owing to well-known small-sample biases induced by the persistence of the dividend-price ratio (Stambaugh (1999)).

The relation (6) can also be tested using pooled time series and cross-sectional data. In the real estate context, such an analysis is potentially much more informative than simply relying on time series averages. In fact, from an investor’s viewpoint, it is much more difficult to construct a diversified portfolio of real estate properties across different areas than to purchase a diversified portfolio of publicly traded equities. Moreover, the geographic, demographic, and economic factors that enter into the pricing of commercial real estate make the portfolio choice problem involving real estate particularly challenging.

2.2 Real Estate Expected Returns, Rents, and Cap Rates Across Metropolitan Areas in the US

The model in the previous section allows us to specify the time series properties and forecasting relations of expected rent growth, cap rates, and expected returns and is applicable to commercial real estate in any metropolitan area. As a starting point, we

³Although ongoing research is revisiting these results (Lettau and Ludvigson (2004)).

consider apartments in two distinct metropolitan areas, say, Portland (denoted by “ i ”) and Dallas (denoted by “ j ”) whose cap rates are expressed as in expression (3). The difference in their cap rates at time t can be written as

$$(cap_{i,t} - cap_{j,t}) = k + E_t \left[\sum_{k=0}^{\infty} \rho^k (r_{i,t+1+k} - r_{j,t+1+k}) \right] + E_t \left[\sum_{k=0}^{\infty} \rho^k (\Delta h_{j,t+1+k} - \Delta h_{i,t+1+k}) \right] \quad (7)$$

where $k \equiv k_i - k_j$, and $cap_{i,t}$ denotes the cap rate in area i at time t .⁴ Expression (7) decomposes the difference in cap rates between regions i and j into differences in expected returns and in expected rental growth rates. For example, suppose that the cap rate of the average apartment in area i is higher than that of the average apartment in area j . This implies that either expected returns of apartments in area i are higher than those in j , or that the future growth rate in apartment rents in area i is lower than in area j , or both.

The difference in cap rates across metropolitan areas in expression (7) depends on the cross-sectional and time series variations in expected returns and expected rent growth rates. To see this, suppose that expected returns in each metropolitan area respond differently to the same underlying fluctuations in x_t

$$E_t r_{i,t+1} = r_i + \delta_i x_t \quad (8)$$

where r_i is the unconditional return and δ_i captures in a reduced-form fashion the sensitivity of expected returns in region i to variation in economic conditions.⁵ In addition, as before, we assume that the expected growth in rents in a given area is

$$E_t \Delta h_{i,t+1} = g_i + \tau_i x_t + \psi y_{i,t-1} + \zeta_{i,t+1} \quad (9)$$

where g_i is the unconditional expected rental growth rate and $\zeta_{i,t+1}$ is an independent shock. It follows then that the cap rate across metropolitan areas can be written as:

$$cap_{i,t} = \left(\frac{r_i - g_i}{1 - \rho} \right) + \left[\delta_i (1 - \tau_i) \frac{x_t}{1 - \rho\phi} - \frac{y_{i,t}}{1 - \rho\psi} \right]. \quad (10)$$

⁴The same convention applies to the remaining terms. This equation is obtained under the assumption that the linearization constant ρ is the same across both markets, which is a realistic assumption in our dataset. Its values range from 0.911 to 0.925 across our sampled markets.

⁵While the economic factors that determine δ_i are certainly of great interest, this is beyond the scope of our study.

In expression (10), the first term captures the difference in the unconditional moments which is simply a log-linearization of the standard Gordon constant-growth model. Clearly, the unconditional difference in cap rates between two metropolitan areas must be due either to differences in expected returns or in expected rental growth rates. The second term in expression (10) captures time-varying expected returns and expected rent growth rates. Metropolitan areas with more variable expected returns (higher δ_i) will have higher cap rates even if the unconditional expected returns and growth rates in the two areas are equal. Similarly, the cap rate will be a better proxy for time varying expected returns in areas where the growth in rents is less influenced by economic conditions (lower τ_i).

Notice that even small fluctuations in expected return can have a large effect on prices so long as these fluctuations are persistent, which as we will see below is an empirically accurate assumption. The amplifying effect is captured by the denominator in expression (10). Hence, the introduction of time-varying expected returns is particularly important for commercial real estate where it has been noted that economic variations have sizeable effects on prices. See, for example, Case (2000) who provides an example illustrating “the vulnerability of commercial real estate values to changes in economic conditions” along with a review of recent boom-and-bust cycles in that market.⁶ Similarly, using international data, Case, Goetzmann, and Rouwenhorst (2000) find that commercial real estate is “a bet on fundamental economic variables”. One of the empirical questions that we tackle below is to investigate how large this effect is likely to be.

2.3 Comparison of Expected Real Estate Returns: Apartments, Retail, Industrial, and Offices

In general, commercial real estate can be divided into five categories: apartments, industrial, retail, offices, and hotels. By their very nature, these property types have different rent and risk characteristics and their sensitivities to economic conditions also vary. In this paper, we restrict our attention to apartments, retail, industrial, and office properties, denoted by superscripts A , R , I , and O , respectively. Unfortunately, we do not have data for hotels but hotels represent less than four percent of the total value of commercial real estate in the

⁶In his example, Case (2000) assumes that expected returns increase and the expected rent growth decreases with economic conditions.

U.S.⁷

The expected return of an apartment in region i at time t can be written as

$$E_t r_{i,t+1}^A = r_i^A + \delta_i^A x_t \quad (11)$$

where r_i^A is the unconditional return to apartments and δ_i^A captures the effect of time variation in underlying economic conditions x_t on apartment expected returns in area i . In many respects, this is a generalization of the framework in the previous section in which the sensitivity of expected returns to economic fluctuations is now allowed to differ not only across metropolitan areas but also across property types.

We allow the growth in rents to differ across commercial real estate types. The rental growth rate of an apartment is

$$E_t \Delta h_{i,t+1}^A = g_i^A + \tau_i^A x_t + y_{i,t}^A$$

and the rent growth of the other property types follow similar processes.

The cap rates of a property type, say, apartments in area i can be expressed as

$$cap_{i,t}^A = \left(\frac{r_i^A - g_i^A}{1 - \rho} \right) + \left[\delta_i^A (1 - \tau_i^A) \frac{x_t}{1 - \rho\phi} - \frac{y_{i,t}^A}{1 - \rho\psi} \right]. \quad (12)$$

The expected returns of property types whose growth in rents are more sensitive to the time-varying economic conditions, τ_i close to one, will not covary with the cap rate. Also the variability of the growth in rents that is orthogonal to expected returns, $y_{i,t}$, also plays an important role in our ability to detect a relation between cap rates and future returns. Since this variability is orthogonal to the cap rate as well as to expected returns, it has the effect of noise in predictive regressions. To the extent that the variability in this component differs across property types, we should expect to see a stronger forecasting relation between cap rates and expected returns for precisely those properties with lower variability in $y_{i,t}$ and a lower total volatility in their rental growth process.

⁷See Case (2000).

3 The Commercial Real Estate Data

Our data consists of prices and annual cap rates of class A apartments, retail, industrial, and offices for fifty-three U.S. metropolitan areas. The data are provided by Global Real Analytics (GRA) and covers the period beginning with the second quarter of 1994 (1994:2) and ending with the first quarter of 2003 (2003:1) at a quarterly frequency. The prices and cap rates for each property category are averages of transactions data in a given quarter. Hence, we have panel data with 1908 observations (36 quarters \times 53 metropolitan areas). We also have a subset of this data for twenty-one of these regions over the time period 1985:4 to 2002:4 but only at a bi-annual frequency. While we have no independent means of verifying the accuracy of the data, it does not, for example, exhibit extreme serial dependence that characterizes appraisal-based datasets. Perhaps a good indication of the data’s accuracy is the fact that it is used by many real estate, financial, and government institutions.⁸

The fifty-three areas cover more than 60% of the U.S. population (2000 data). A full description of the metropolitan areas is included in Appendix 1. Given the annual cap rates, CAP_t , and prices, P_t , of a property type in a given area, we construct net rents in that quarter from expression (1) as $H_t = CAP_t P_{t-1}/4$.⁹ The gross returns $1 + R_t$ in quarter t are then obtained from equation (1) and one plus the growth in rents is H_t/H_{t-1} . For consistency with the expressions in the previous section, we work with log cap rates, $cap_t = \ln(CAP_t)$ and log rent growth rates, $\Delta h_t = \ln(H_t/H_{t-1})$. Also, we use log excess returns, $r_t = \ln(1 + R_t) - \ln(1 + R_t^{Tbl})$, where R_t^{Tbl} is the three-month Treasury bill yield. By way of convention, we use lower cases to denote the log transformation of the variables. Appendix 1 also reports time series averages of excess returns, rent growth rates, and cap rates for all property types and metropolitan areas.

We compute autocorrelations of the excess returns series for each property type in each area. In Table 1, Panel A, we summarize the autocorrelation structure of excess returns at different quarterly lags (k). At each lag, we display the 25th, 50th, and 75th percentiles of the autocorrelations across all regions. In addition, we display the number of correlations

⁸A partial list of the subscribers is: Citigroup, GE Capital, J.P. Morgan/Chase, Merrill Lynch, Lehman Brothers, Morgan Stanley Dean Witter, NAREIT, Pricewaterhouse-Coopers, Standard & Poors, Trammell Crow, Prudential RREEF Funds Capital/Real Estate Investors, Washington Mutual, FDIC, CalPERS, and GMAC, and many others. GRA is teamed with CB Richard Ellis and Alliance Capital Management. The wide use of the GRA dataset also indicates that there are no better and readily accessible alternatives. To our knowledge, this is the first academic study to use this dataset.

⁹We obtain very similar results by modifying the timing as $H_t = CAP_t P_t/4$

that are significantly different from zero at the 5% level (denoted by \mathcal{N}) and specify the number significantly positive (denoted by +) and negative (denoted by -). For apartments, the median autocorrelation at a one quarter lag is -0.007 and the inter-quartile range is -0.101 to 0.170 . The number of areas to exhibit serial correlation at a one quarter lag is five, with four being positive. In the case of industrial properties, retail properties, and offices buildings, the median first order autocorrelations are higher at 0.043 , 0.168 , and 0.287 , respectively. For retail properties, out of the eight significant first-order autocorrelations, all eight are positive. Similarly, for offices, out of the twenty-five significant autocorrelations, twenty-four are positive.

The autocorrelations for all property types decrease rapidly with increasing lag even for office buildings which display the highest degree of serial dependence.¹⁰ In general, after three quarters to one year the median autocorrelation and the number of significant correlations are small. Taken together, these results indicate that while there is some degree of positive serial dependence in our commercial real estate returns at a quarterly lag, returns are essentially uncorrelated at lags of one year or greater. Therefore, we conclude that our commercial real estate data does not exhibit severe price rigidities.

We summarize the serial dependence of rent growth and cap rates in Panels B and C of Table 1, respectively. For the rent growth rates across areas, the median first order autocorrelations are 0.078 (apartments), 0.049 (industrial), 0.041 (retail), and 0.119 (offices), where most of the significant values come from positively autocorrelated series. Interestingly, retail properties and office buildings show less persistence in rent growth than in returns at the one quarter lag. For lags of three quarters to one year, the rent growth series exhibit no serial correlation. In contrast, the cap rate data is very persistent for all four property types with median one quarter autocorrelations of 0.815 (apartments), 0.744 (industrial), 0.834 (retail), and 0.817 (offices). At a one quarter lag, almost all fifty-three series exhibit significant positive serial correlation across all property types. The positive serial correlations in cap rates persist for the first two years.

We conclude this section with several additional observations about our data. Firstly, the properties that we consider are mostly held by corporations and other large investors. Hence, it is not surprising to see less serial correlation than in single family home data (Case and Shiller (1989)) where market inefficiencies and frictions undoubtedly play a larger role. Since we are dealing with a disaggregated dataset covering fifty-three metropolitan areas,

¹⁰For offices, almost half of the series exhibit significantly positive serial correlation at a one quarter lag.

the time series properties of each single series would be far noisier than if we were to consider an average of these series. However, as mentioned previously, a cross-sectional investigation of real estate dynamics is much more informative in light of the difficulties in creating a diversified portfolio of such assets.

4 Predictive Regressions

A central question of this paper is whether the cap rate in a given real estate market reflects investors' expectations of future returns or growth in rents. The framework in Section 2 suggests the following two cross-sectional regressions

$$r_{i,t+1 \rightarrow t+k} = \alpha_k + \beta_k (\text{cap}_{i,t}) + \varepsilon_{i,t+k} \quad (13)$$

$$\Delta h_{i,t+1 \rightarrow t+k} = \mu_k + \lambda_k (\text{cap}_{i,t}) + v_{i,t+k} \quad (14)$$

where expected returns and rent growth rates are proxied by $r_{t+1 \rightarrow t+k} \equiv \sum_{l=0}^k r_{t+1+l}$ and $\Delta h_{t+1 \rightarrow t+k} \equiv \sum_{l=0}^k \Delta h_{t+1+l}$, respectively. We run these regressions for various horizons k using the pooled sample of fifty-three metropolitan areas over the 1994 to 2003 sample period for each of the four property types. The pooled data are first stacked for all areas in a given quarter and then for all quarters. The results are reported in Tables 2 and 3. There we report for various horizons k the least squares estimates which are consistent and efficient if the regression residuals in the equations are cross-sectionally homoscedastic and serially uncorrelated. Since the residuals are serially correlated by construction, we report Newey-West t -statistics which correct for serial correlation induced by the overlapping nature of the observations, the t/\sqrt{k} statistic which offers an even stronger correction for the overlap (Torous, Valkanov, and Yan (2005)), the corresponding goodness-of-fit measure, R^2 , and the number of observations, N , in the pooled regression. We will primarily focus on the more conservative t/\sqrt{k} statistic (which has an asymptotically normal distribution) and the R^2 statistic because the overlap is a non-trivial part of the sample.¹¹

Table 2 presents the results of forecasting future returns using the cap rate (expression (13)) for apartments, industrial properties, retail properties, and office buildings. At horizons of less than one year ($k < 4$ quarters), the cap rate is positively correlated with future returns

¹¹Later we demonstrate that our findings are robust to various econometric refinements, such as, for example, cross-sectional correlation in the residuals.

but the R^2 statistics are low across all property types. This short-horizon predictability partially reflects the serial correlation in returns at lags of one to three quarters observed in Table 1. In the apartments data for $k \geq 4$, the β estimates increase from 0.275 at a yearly horizon to 0.961 at a five year horizon and these estimates are statistically significant even when relying on the more conservative t/\sqrt{k} statistic. The R^2 s of the regressions also increase to 0.166 at the five year horizon. In the case of industrial and retail properties, cap rates best predict future returns at horizons of between two and four years. The highest β estimate for industrial properties is 0.946 at $k = 16$ quarters with an R^2 of 0.129. For retail properties, the highest β estimate is 1.098 at $k = 12$ quarters with an R^2 of 0.246. In both cases, the t -statistics are statistically significant. In contrast, for offices, there does not appear to be evidence of predictability at any horizon. The highest β estimate in the case of offices is 0.346 at the two year horizon with a significant t -statistic, but the corresponding R^2 is only 0.035. At longer horizons, the coefficients for offices are indistinguishable from zero.

As the horizon increases, the number of observations in the predictive regressions decreases even though we compute $r_{t+1 \rightarrow t+k}$ and $\Delta h_{t+1 \rightarrow t+k}$ with overlapping data. The last column of each Table shows that at the one year horizon we have 1643 observations while only 795 observations are available at the five year horizon. This smaller number of observations reduces the power of our tests and should work against our detecting predictability especially since we rely on conservative statistics to correct for the effects of overlap.¹²

The results in Table 2 suggest that at least for apartments, industrial properties, and retail properties, cap rates reliably forecast returns at horizons of between three and five years.¹³ For office buildings, by contrast, there is minimal evidence of predictability at any horizon $k \geq 4$ quarters. Recall from expression (3) that the presence of predictability and its magnitude depend critically on the forecastability of rent growth and on the persistence of the cap rate. The precision of the β estimates also depends on the variability of the rent growth process. Our results suggest that office buildings differ from the other property types both in the variability of their rent growth and in the persistence of their cap rates.

¹²Torous, Valkanov, and Yan (2005) show that the t/\sqrt{k} test might be conservative in small samples when the overlap is a significant fraction of the sample size. For larger samples, the test is correctly sized.

¹³It is interesting to note that we find somewhat similar β estimates to those reported in the stock predictability literature. For example, Campbell, Lo, and MacKinlay (1997) report coefficients estimates of 0.329, 0.601, 0.776, and 0.863 at the one, two, three, and four year horizons, when forecasting stock returns (these numbers refer to the period 1952-1994). These values are very similar to ours reported in Table 2 and similar patterns are displayed also for the R^2 statistic.

In Table 3, we present the results of estimating expression (14). It is immediately evident that for apartments, industrial properties, and retail properties, cap rates do not forecast the future growth in rents at long horizons. In particular, the t/\sqrt{k} statistics under the null that $\lambda = 0$ are not significantly different from zero at horizons of between three and five years and the corresponding R^2 s statistics are between 0.000 and 0.035. At horizons of less than one year, only the apartments coefficients are significant, but the R^2 statistics are no larger than 0.020. For offices, the λ estimates are negative but insignificant. The R^2 statistics increase with horizon, reaching a value of 0.077 at a horizon of $k = 20$ quarters. The t/\sqrt{k} statistic at this horizon is -1.817 and is significant at the ten percent level. From this evidence, we conclude that for apartments, industrial properties, and retail properties, there is little or no evidence that cap rates can forecast the future growth in rents. For office buildings, the evidence is also very weak but, unlike the other property types, the estimates have the theoretically correct sign.

Expressions (13) and (14) can be thought of as cross-sectional regressions estimated once a quarter whose coefficients are then averaged over time, similarly to the Fama and MacBeth (1973) procedure. The estimates from our pooled regressions should be identical to those obtained from the corresponding Fama and MacBeth (1973) regressions if the cap rates do not vary with time (Cochrane (2001)). In fact, the Fama-MacBeth procedure gives very similar results when applied to our data. For example, in the case of apartments at the five year horizon, we obtain a Fama-MacBeth estimate of 0.750 instead of 0.961. The corresponding Fama-MacBeth t -statistic of 8.334 is larger than the ones reported in Table 2 because it does not correct for the serial correlation induced by the data overlap. When we do so using a Newey-West correction, we obtain a t -statistic of 6.367, which is slightly higher than the value of 5.045 in our Table. Since we obtain similar results at all horizons and across property types, we believe the statistical significance of our results is quite conservatively stated.

It is important to emphasize that the pooled regressions differ from the time series regressions used in the stock return predictability literature. Given the limited time period spanned by the data, our approach has several advantages. Firstly, as we are primarily interested in long horizon relations but don't have a long enough dataset to run time series regressions, the only way of exploring these relations is to rely on pooled data. Second, since we do not exclusively rely on time series regressions, we are less prone to biases induced by the persistence of the rent-price ratio (Stambaugh (1999)). Third, as shown below, there is

considerable heterogeneity in cap rates, returns, and rent growth rates across metropolitan areas at a particular point in time. Therefore, forecastability tests based on the pooled regressions are likely to have higher power than tests based on time series regressions in which the dividend price ratio has only a modest variance (Torous and Valkanov (2001)).

4.1 Robustness

4.1.1 Fixed Effects

It is clear from equation (10) that cap rates capture not only time-variation in expected returns but also cross-sectional differences.¹⁴ Since the cross-sectional differences are likely related to various demographic, geographic, and economic factors, it is more plausible that rents and prices are quicker to adjust to time series shocks in a given metropolitan area than to variations across metropolitan areas. To allow for the possibility of unobserved heterogeneity across regions, we add fixed effects to the previous regressions:

$$r_{i,t+1 \rightarrow t+k} = \alpha_k + \beta_k (\text{cap}_{i,t}) + \varphi_i + \tilde{\varepsilon}_{i,t+k} \quad (15)$$

$$\Delta h_{i,t+1 \rightarrow t+k} = \mu_k + \lambda_k (\text{cap}_{i,t}) + \varsigma_i + \tilde{v}_{i,t+k} \quad (16)$$

where the fixed effects φ_i and ς_i capture the heterogeneity across metropolitan areas. We estimate the regressions by including fifty-three area-specific dummy variables in the regressions.

Table 4 presents the results of estimating the fixed effects regression (15).¹⁵ The regressions are estimated by first regressing excess returns and dividend growth rates on the cross-sectional dummies and then regressing the residuals on the cap rates. Notice that the β estimates do not change dramatically in magnitude from their previous values. As to be expected with a fixed effects model, the Newey-West corrected t statistics, t_{NW} , and the t/\sqrt{k} statistics are now slightly lower. However, the predictive power of the cap rates is still evident in the case of apartments, industrial, and retail properties. We conclude that unobserved heterogeneity across metropolitan areas is unlikely to account for our findings.

¹⁴Which are captured by the first term in expression (10).

¹⁵We do not report the results of estimating the fixed effects regression (16). Recall that in the absence of fixed effects, the coefficients are insignificant. Adding these fixed effects will only reduce their significance even further.

4.1.2 Longer Sample Period with Fewer Metropolitan Areas

A natural question to pose is whether our results hold over a longer sample period or are specific to our choice of the 1994 to 2003 sample period. Indeed, this particular sample period contains but only one full business cycle and coincides with a general upward trend in real estate prices.

To answer this question, we extend the sample back to 1985 by augmenting our data with the bi-annual observations on all of the property types available for a subset of twenty-one of the fifty-three metropolitan areas. These data are available from the second half of 1985 to the first half of 1994 and to this we add the post-1994 data for these twenty-one areas sampled at a bi-annual frequency. This gives a sample spanning the 1985 to 2002 time period containing thirty-five semi-annual observations for the twenty-one areas for a total of seven hundred and thirty-five observations for each property type. By relying on this dataset we can investigate the stability of our predictability findings but at a cost of fewer cross-sectional observations.

We re-estimate regressions (15) and (16) with the 1985 to 2002 dataset using twenty-one fixed effects. The results from regression (15) are presented in Table 5. For all property types, cap rates forecast future returns and the predictability increases with the forecasting horizon. The β estimates are similar to these reported in Tables 2 and 4, especially at short horizons. For example, for apartments the β estimate at the one year horizon is 0.261 with a t/\sqrt{k} statistic of 4.499 and an R^2 of 0.057. Similar comparisons hold for the other property types. At longer horizons, the estimates are larger in magnitude and even more significant. For example, for industrial properties at the five year horizon, the β estimate is 2.083 with a t/\sqrt{k} value of 4.828 and an R^2 of 0.317. It is also worth noting that future office returns, while still the least predictable of all four property types, are also forecastable than in the 1994 to 2003 sample period.¹⁶ We conclude that the ability of cap rates to capture future fluctuations in commercial real estate returns does not appear to be driven by the 1994 to 2003 sample period. If anything, the evidence of predictability is even stronger in the longer dataset.¹⁷

¹⁶The results from forecasting dividend growth are insignificant and are omitted. They are available upon request.

¹⁷The relatively stronger results over the longer sample period can be understood if we recall that during the 1994 to 2003 sample period real estate valuations were generally trending up despite already low cap rates. Hence, predictability is even harder to detect.

4.1.3 Other Robustness Checks

In this section, we describe several other robustness checks used to ensure the reliability of our empirical results. We will discuss these results without detailing them in Tables as they are in general agreement with our previous findings.

First, we run the forecasting regressions using only non-overlapping returns. The predictive power of the cap rates remains. In particular, we obtain β estimates that are similar to these already reported above and in fact, for longer horizons, the estimates and corresponding t_{NW} statistics are larger than obtained when using the overlapped returns. However, these results should be interpreted with some caution as the number of observations at longer horizons is rather small.¹⁸

In the pooled regressions, all observations are weighted equally. This estimation approach is efficient under the assumption that the variances of the residuals are equal across regions. The homoscedasticity assumption may not be appealing in this case as larger metropolitan areas are generally more diverse resulting in more heterogeneity in the quality of a given property type. For example, it is unlikely that the variance of residuals for Los Angeles will be the same as that of, say, Norfolk, Virginia. To address this concern, we rely on weighted least squares under the assumption that the heteroscedasticity in the residuals is proportional to the population in a given area. In particular, the weight given to a metropolitan area is given by that area's population over the total population of all metropolitan areas in the previous year. We then divide the left- and right-hand side variables of our predictive regressions (13) and (14) by the square root of the computed weights. Interestingly, the β estimates increase in magnitude but the corresponding t/\sqrt{k} statistics are very similar. The results for dividend growth are once again insignificant.

We also estimate regressions (13) and (14) with a feasible generalized least squares (FGLS) estimator which allows the residuals to be cross-sectionally correlated. The FGLS estimates and standard errors are computed using an iterative procedure. In the first stage, we compute the least squares estimates and the residuals from these regressions are used to form an estimate of the covariance matrix. We then use the estimated covariance matrix in a generalized least squares procedure to compute new estimates and residuals, which are then used to obtain a new estimate of the covariance matrix. This procedure is repeated until the estimates converge. The predictive regression estimates and t/\sqrt{k} statistics that

¹⁸For example, for the nine full years in the 1994 to 2003 sample, we have only one five year return.

we obtain in this fashion are similar to those reported above.¹⁹

As a final remark, note that there are no efficiency gains to be had from estimating regressions (13) and (14) jointly. In fact, given that the right-hand side variables are the same, the joint seemingly unrelated equations (SUR) estimator is identical to our equation by equation estimator.

5 Economic Significance of the Predictability

From an economic perspective, it is easier to interpret the response of future returns to changes in cap rates rather than log cap rates. To do so, we divide the estimated β_k coefficients by the average cap rate, or β_k/cap where *cap* is expressed in the same units as the returns (see, e.g., Cochrane (2001)). We compute the transformed coefficients $\beta_k/(cap)$ for apartments, industrial properties, retail properties, and office buildings using the corresponding β_k estimates from Table 2 and their average cap rates 8.7%, 9.1%, 9.2%, and 8.7%, respectively.²⁰ For apartments, a small increase in the cap rate implies that expected returns should increase between 2.209 times, if we take the five year estimates ($0.961/(5 \times 0.087)$), and 3.161 times, if we take the one year estimates ($0.275/0.087$). Similarly, for industrial properties, retail properties, and office buildings, the sensitivities are 4.077, 4.511, 2.333, respectively, if we rely on the one year estimates, and 1.875, 1.863, 0.462, respectively, if we use the five year estimates.

Based on these calculations, there appears to be a difference between the predictability of apartments, industrial properties, and retail properties versus office buildings. For the first three property types, the sensitivities are between factors of 2 and 4 whereas for offices they are in the range of between 0.5 and 2. Based on this, it is tempting to conclude that expected returns of office buildings are much less time-varying. However, such a comparison assumes that the rent growth of all property types are not only equally unforecastable but that they are also equally volatile. However, in the next section, we show that while the rent growth rate of offices is unforecastable, it is much more volatile than the rent growth rate of the other property types.

¹⁹The Fama-MacBeth estimates that we previously described are another way of addressing cross-sectional correlation (Cochrane (2001)) and the results are again unchanged.

²⁰From the Table in the Appendix.

The observed time variation in expected returns has a large effect on the variability of commercial real estate prices. A one percentage point increase in expected returns results in a 2 to 4 percentage point increase in the current valuations of apartments, industrial, and retail properties. This high variability of prices is largely due to the persistence of expected returns. Even small deviations of expected returns from their unconditional mean will persist for a considerable period of time, with a half life of 1.5 years, and would thus have a significant effect on prices.

To further appreciate the effect of time-varying expected returns on commercial real estate, it is useful to compare our results to those in the stock market literature. For the aggregate stock market, a one percentage point increase in expected returns results in about a 4 to 6 percent increase in prices (see, e.g., Cochrane (2001) for a summary of the evidence).²¹ Hence, the sensitivity of commercial real estate prices to changing expected returns is not very different than that of common stock, albeit it is lower. To the extent that the fluctuations in expected returns of the stock market and commercial real estate are both driven by changing economic conditions²², our findings suggest that an investment in commercial real estate is not necessarily an adequate hedge against stock market risk.

6 Understanding the Results

Thus far we have documented that for apartments, industrial properties, and retail properties, cap rates are significantly correlated, both statistically as well as economically, with their future returns but not with their future growth in rents. For offices, cap rates do not forecast either future returns or future growth in rents. Two immediate questions arise. First, do cap rates proxy for demographic, geographic, economic or other cross-sectional differences in commercial real estate prices, or do they capture time variation in expected returns? Second, why are the results for office buildings so different from the other property types?

²¹The difference in magnitudes is due mainly to the fact that the dividend yield of the market is about 4 percent, which is half of the cap rate of commercial properties.

²²Which is something we verify later in the paper.

6.1 Is Predictability Due to Time-Varying Expected Returns?

The predictability we have documented is due either to cross-sectional differences in unconditional returns or to time series variation in conditional returns. To understand this point, suppose that for a given property type, the cap rate at time t in area i is higher than that in area j . From expression (10), the relatively lower price in area i can either be due to a lower unconditional expected return or to a higher unconditional expected growth in rents in area i . These cross-sectional pricing differences are not a function of time.

Cross-Sectional Controls

The pricing of commercial and residential real estate across metropolitan areas and its relation to demographic, geographic, and economic variables has been widely investigated. For example, Capozza, Hendershott, Mack, and Mayer (2002) find that home pricing dynamics vary with city size, income growth, population growth, and construction costs. Abraham and Hendershott (1996) document a significant difference in the time series properties of house prices in coastal *versus* inland cities. Lamont and Stein (1999) show that house prices react more to city-specific shocks, such as shocks to per-capita income, in regions where homeowners are more leveraged.²³ In light of this evidence, one cannot help but wonder whether cap rates are not merely proxying for some of these cross-sectional effects as opposed to capturing time variation in economic conditions.²⁴

To test this “proxy” hypothesis, we use demographic, geographic, and economic variables to capture differences across metropolitan areas. More specifically, for each metropolitan area, we use the following variables: population growth, $gpop_t$, the growth of income per capita, $ginc_t$, and the growth of employment, $gemp_t$, all of which are provided by the Bureau of Economic Analysis at an annual frequency. We also use the annual growth in construction costs, gcc_t , from R.S. Means. The construction cost indices include material costs, installation costs, and a weighted average for total in place costs.²⁵ In addition, after lagging by two periods, we include log population, pop_{t-2} , log per capita income, inc_{t-2} , log

²³While most of the cited papers focus strictly on the residential market, similar mechanisms are likely at play in commercial real estate.

²⁴Which are captured by the second term in equation (10).

²⁵There are missing data for some metropolitan areas in our construction costs database. For these series, we assigned the values of the closest area for which data is available. In detail, we assigned to Oakland and San Jose the value of San Francisco, to Nassau-Suffolk the values of New York City and to West Palm Beach the values of Miami. For the areas where merged data is present in the real estate database, a unique index is constructed as weighted average of the single areas’ construction costs, based on their population.

employment, emp_{t-2} , and log construction costs, cc_{t-2} , to proxy for the level of urbanization (Glaeser, Gyourko, and Saks (2004)). We lag these level variables by two periods to prevent a mechanical correlation with corresponding growth rates. We also include a dummy variable $coast_t$ which equals one when the metropolitan area is in a coastal region.²⁶ These data are available at annual frequency until the end of 2001.

We then account for cross-sectional differences by augmenting the regressions (13) and (14) as follows:

$$r_{i,t+1 \rightarrow t+k} = \alpha_k + \beta_k (cap_{i,t}) + \theta'_k X_{i,t} + \varepsilon_{i,t+k} \quad (17)$$

$$\Delta h_{i,t+1 \rightarrow t+k} = \mu_k + \lambda_k (cap_{i,t}) + \theta'_k X_{i,t} + v_{i,t+k} \quad (18)$$

where $X_{i,t}$ is a set of pre-determined characteristics. If cap rates are solely proxying for differences across metropolitan areas but are not capturing time variation in expected returns, then the inclusion of these cross-sectional proxies will decrease the significance of the estimated cap rate coefficients while increasing the regression's R^2 . Similarly, under the proxy hypothesis, the exclusion of the cap rate from these regressions should not significantly alter the R^2 statistic.²⁷

The results of estimating regressions (17) and (18) at a four year horizon ($k = 16$ quarters) are presented in Tables 6 and 7, respectively. For each property type, we run three specifications. The first includes the cap rate as well as the growth rates of the economic variables ($gpop$, $gemp$, $ginc$, and gcc). In the second specification, we add the levels of these variables and the coastal dummy (pop , emp , inc , cc , and $coast$). The third specification includes the growth rates and the levels but excludes the cap rate.

Table 6 present the results of forecasting expected returns. Several results emerge. First, the growth rate variables are not found to be significant for any of the property types

²⁶We also collected data on financing costs in various metropolitan areas, but there was very little variation across metropolitan areas. Time series variation in interest rates is already captured as we compute all returns in excess of the Tbill rate. We also tried including the rent-to-income variable, which can be motivated from the results in Menzly, Santos, and Veronesi (2004). However, this variable was highly correlated with some of the other controls and we decided against including it in the regressions.

²⁷The fixed effect regressions previously discussed can also be interpreted as tests of the proxy hypothesis. The fixed effects capture the cross-sectional differences of unconditional expected returns and unconditional growth in rents without specifying their origin. Recalling the results from Table 4, we observe that accounting for cross-sectional differences does not significantly decrease the forecasting power of the cap rate. The drawback of this approach is that the dummy variables are simply too coarse to capture variation that can be better explained if we specify the correct source of heterogeneity.

nor does their inclusion affect the R^2 statistics. Second, the inclusion of the levels of the control variables increases the regression R^2 s, but their coefficients are only significant in the case of office buildings. This result may be due to a strong correlation between the control variables. For offices, the control variables are significant which indicates that there is heterogeneity across metropolitan areas. Third, the exclusion of the cap rate leads to a dramatic drop in the R^2 s for apartments, industrial properties, and retail properties. Hence, after accounting for cross-sectional differences in these metropolitan areas, cap rates do capture additional time variation. In the case of office buildings, the exclusion of the cap rate does not lead to a significant drop in the R^2 statistic.²⁸ The results are similar at other return horizons. Taken together, the evidence in Table 6 suggests that cap rates are proxying for more than simply differences in expected returns across metropolitan areas.

Table 7 presents the results for forecasting the growth in rent over a four year horizon. The addition of the controls does not significantly alter the significance of the cap rate. The growth and levels of the control variables increases the R^2 s from a range of three to four percent (Table 3) to between sixteen and twenty-seven percent, depending on the property type with retail having the highest R^2 . Several control variable coefficients are now significant, depending on the property type and the particular specification.²⁹ The office building regressions have the highest number of significant control variable coefficients, suggesting that for these properties cross-sectional differences in economic conditions are significant determinants of the future growth in rents. Interestingly, the exclusion of the cap rate from the regressions does not result in a dramatic drop in R^2 s as was the case for expected returns. Hence, it seems that the expected growth in rents for all commercial property types is determined by area-specific characteristics.

Time-Variation in Expected Returns

Cap rates for apartments, industrial, and retail properties are able to capture fluctuations in time-varying expected returns. Expected growth in rents, by contrast, appears to be determined by cross-sectional determinants and does not seem to fluctuate over time. To more directly verify this claim, we regress future one year returns and future rent growth rates on regional dummies and variables that have been documented to capture time-varying economic conditions. This regression is motivated by expressions (8) and (11).

²⁸We cannot interpret the signs on the economic variables since we do not have a model and the lead and lag effects make it even more difficult to interpret.

²⁹But the issue of collinearity remains.

The conditioning information includes the term spread, the default spread, the CPI inflation rate, and the three-month Treasury bill rate.³⁰ These variables have been widely used in the stock predictability literature to capture time-varying behavior in aggregate stock market expected returns (Campbell and Shiller (1988a), Campbell (1991), Fama and French (1989), Torous, Valkanov, and Yan (2005) and, for a good review, Campbell, Lo, and MacKinlay (1997)). The term spread is calculated as the difference between the yield on 10-year and 1-year Treasuries. The default spread is calculated as the difference between the yield on BAA- and AAA-rated corporate bonds. The CPI inflation is the quarterly growth in the CPI index.³¹ Under the hypothesis that expected returns are time-varying, they should be forecasted by the macroeconomic variables. Similarly, we expect these variables to have only modest power in forecasting future rent growth. In estimating these regressions, we use the longer sample period 1985 to 2003 (with fewer metropolitan areas) in order to obtain more precise estimates of the parameters because the regressors vary across time but are the same for all metropolitan areas.

We present the results from these regressions in Table 8. Focusing on panel A in Table 8, we see that future returns of apartments, industrial properties, and retail properties are explained by time variation in the term spread, default spread, inflation, and the short interest rate. Taken together, the macroeconomic variables explain between ten and twenty-four percent of the time series fluctuations in cap rates for these property types. It is interesting to note that for office buildings approximately twenty-three percent of the time series fluctuations in future returns is explained by the macroeconomic variables. Therefore, the ability of the macroeconomic variables to capture variations in future office returns are comparable to those for apartments and retail properties. Industrial properties have the lowest R^2 in the regressions. These results suggest that office expected returns are time-varying.³²

The estimated coefficients are significant and positive for the term spread, negative for the default spread, and negative for inflation. Interestingly, the same signs are observed

³⁰We also tried using the consumption-wealth variable “cay,” which Lettau and Ludvigson (2001) show forecasts future aggregate stock market returns. In the specification with the term spread, default spread, inflation, and the short rate, the cay variable was not significant. However, it was significant if any one of the other variables was dropped.

³¹All these data, except the three-month Treasury bill rate, are from the FRED database. The three-month Treasury bill rate is obtained from Ibbotson Associates. The statistical properties of these variables are well known and are not provided here.(see, e.g., Torous, Valkanov, and Yan (2005)).

³²The results from the shorter 1994-2003 sample are very similar, albeit less significant, with R^2 s in the range of between ten and fifteen percent.

when expected stock returns are correlated with these variables (Campbell (1987), Fama and Schwert (1991), Fama and French (1989), Fama (1981), and Keim and Stambaugh (1986)). Hence, our results are not only consistent with cap rates capturing time variation in the expected returns of these property types, but they also imply that expected returns of stocks and commercial real estate are positively correlated in their response to changing economic conditions. This suggests that investment in commercial real estate may not provide an adequate hedge against adverse movements in stock returns that are due to changes in macroeconomic conditions.

Panel B of Table 8 presents the results of forecasting the yearly growth in rents with the macroeconomic variables. In contrast to the results of Panel A, the economic variables have much less ability in predicting the future growth in rents of apartments, industrial properties, and retail properties. The goodness of fit in these regressions is in the range of between four and seven percent. For office buildings, we observe a much stronger forecastability of growth in rents. The corresponding R^2 of 13.5 percent is about twice as large as that of other property types with most of the forecastability being driven by the default spread and inflation. As we discuss in the next section, this difference is important in understanding the lack of expected return forecastability observed for offices.

6.2 Why are Offices so Different?

A recurring theme in our discussion thus far has been the difference between office buildings and the other property types. Only for office buildings do we fail to detect an economically and statistically significant relation between cap rates and future returns. Based solely on this evidence, concluding that the expected returns of offices are less susceptible to economic fluctuations than are the other property types would only be true if expected growth in rents for *all* property types are: (i) *equally* correlated with expected returns; and (ii) *equally* volatile. To see the necessity of assumption (i), consider expression (12) and suppose that expected returns of offices and, say, apartments are equally exposed to economic variation ($\delta^A = \delta^O$). In addition to expected returns of offices and apartments being equally time-varying, we assume that the growth in rents of offices is much more correlated with expected returns than is the growth of apartments ($\tau^O = 1$ while $\tau^A \approx 0$), and that the variation in rent growth that is orthogonal to x_t is the same for offices and apartments ($V(y_t^O) = V(y_t^A)$). Under these assumptions, the cap rate will be a better predictor of expected returns for

apartments despite the fact that the expected returns of both property types are time-varying. This result obtains because the variability in expected returns for offices is offset by the variability in rental growth and the net effect, captured by $x_t(1 - \tau^O)$, results in no variability in their cap rates. This argument has been made for the aggregate stock market by Campbell and Shiller (1988b) and more explicitly by Lettau and Ludvigson (2004) and Menzly, Santos, and Veronesi (2004).

Assumption (ii) must also hold if different property types are to comparably predict future returns. Using similar logic, suppose that the variability of rent growth in offices that is orthogonal to economic conditions is greater than of, say, apartments ($V(y_t^O) > V(y_t^A)$), while their expected returns are equally time-varying ($\delta^A = \delta^O$). From expression (12), it would still be the case that the cap rate of apartments will be a better predictor of expected returns. The extra variability in the rent growth of offices that is orthogonal to the variation in expected returns will only add extra noise and so will decrease the power of the predictability tests.

Table 8 provides evidence against assumption (i). Panel B of that Table shows that the rent growth of offices is much more forecastable by macroeconomic variables than is the rent growth of the other three property types. Moreover, it is interesting to note that the same variables that forecast office rent growth also forecast future returns of offices. In particular, the default spread and inflation are both negatively correlated with future office rent growth as well as future returns. This evidence suggests that the rent growth of office buildings is time-varying and is also correlated with office expected returns. As noted earlier, this correlation would make it difficult to detect predictability using office cap rates even if the expected returns of offices are time-varying.

The second assumption is also not supported by the data as the growth of office rents is more volatile than the other property types. To document this fact, we estimate the volatility of rent growth that is orthogonal to economic fluctuations for each property type in each metropolitan area using the time series data from 1985 to 2003. We do so by first regressing the one year rent growth rates of the properties on macroeconomic variables as in Table 8. Using the residuals from these regressions, we estimate GARCH(1,1) models, which yield fifty-three time series estimates of volatilities for each property type. We then compute the median and the mean filtered volatility across metropolitan areas for each property type.

The results are plotted in Figure 1. It is immediately evident that the median and

mean standard deviation for office buildings (solid line) are almost always greater than for the other property types. Moreover, office buildings exhibit more conditional autoregressive heteroscedasticity than the other series. Notice that during the 1991 to 1993 and the 1997 to 1999 periods, the volatilities of office rent growth were particularly high. The first time period was a declining market and plummeting rents while the second was an increasing market with increasing rents (Case (2000)). The mean values of these volatilities across time are 7.0 percent, 7.1 percent, and 5.6 percent annually for apartments, retail, and industrial properties, respectively. For offices, the volatility is significantly higher at 8.5 percent. As a comparison, we also computed the dividend growth rate of the CRSP value-weighted index, a proxy for the aggregate stock market. The volatility of the stock market's dividend growth rate that is orthogonal to the macroeconomic variables over that period is only 8.1 percent. The evidence of high volatility in office rent growth is also consistent with the fact that commercial mortgage-backed securities collateralized by office buildings are viewed as being a much riskier investment than securities collateralized by the other three property types.³³

In summary, the exposure of expected returns of offices to macroeconomic variables appears comparable to that of the other property types. Given that the growth in office rents is more correlated with expected returns and that this growth rate is generally more volatile, it is not surprising that office cap rates are unable to forecast future returns.

7 Conclusions

There are good reasons to believe that the expected returns and rent growth rates of commercial real estate are time-varying. This paper empirically analyzes the fluctuations in returns and rent growth rates for apartments, office buildings, retail properties, and industrial properties. Using the dynamic Gordon model, under certain assumptions the cap rate must forecast time variation in either expected returns or expected rent growth. We find that for apartments, retail properties, and industrial properties, the cap rate forecasts time variation in expected returns but does not forecast expected rent growth rates. For these property types, the time variation in expected returns is important enough to generate significant movements in their prices. For offices, by contrast, the cap rate forecasts neither expected returns nor rent growth rates. Ours is the first study to document the predictability in

³³See, Duff and Phelps Credit Rating Co., *The Rating of Commercial Mortgage-Backed Securities*, 1999.

commercial property returns and to document its large impact on the prices of apartments, retail, and industrial properties.

Our commercial real estate data offers a natural setting in which to demonstrate that the predictability of expected returns by the cap rate, that is the dividend-price ratio, is sensitive to the assumption that the growth rate of cash flows (in our case rents) is unforecastable as suggested earlier by Campbell and Shiller (1988b) and more recently argued by Lettau and Ludvigson (2004) and Menzly, Santos, and Veronesi (2004). We demonstrate that while the expected returns of the four commercial property types have similar exposures to macroeconomic variables, their rental growth rates differ in terms of their correlations with expected returns as well as in their volatilities. As a result, the cap rate for offices, whose rent growth rate is the most highly correlated with expected returns and is also the most volatile, does not forecast expected returns even though these returns are themselves time-varying. The economic sources behind the cyclical variations of office growth rates is an interesting question for future research. Since the cap rate cannot capture variation in expected returns under certain circumstances, it is natural to ask whether there is a variable that is better suited for this task. To answer this question, an extension of the Menzly, Santos, and Veronesi (2004) model to the case of commercial real estate would be an interesting problem to pursue in future work.

We also find that the expected returns of commercial real estate and common stock have similar correlations with macroeconomic variables. In addition to the evidence that expected returns of commercial real estate are time-varying, this finding suggests that commercial real estate may not provide a good hedge against stock market and global economic fluctuations. While this paper deals exclusively with the implications of our findings on the pricing of commercial real estate properties, the portfolio choice problem involving commercial real estate is also very interesting and is left for future research. Some work incorporating real estate already exists in this area (Piazzesi, Schneider, and Tuzel (2003) and Lustig and Van Nieuwerburgh (2004)), but its focus is residential real estate. Future research in this area should further explore the role of commercial real estate and its stochastic properties in a portfolio setting.

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Table 1: Autocorrelation Coefficients of Excess Returns, Rent Growth, and Log Cap Rates

The table reports the autocorrelation coefficients of excess returns (Panel A), rent growth (Panel B) and log cap rates (Panel C) for apartments, industrial, retail, and office properties. Excess returns are computed by subtracting the log total real estate return from the log three-month Treasury bill rate. We first compute the autocorrelation coefficients for each time series of metropolitan area, then consider the cross-sectional coefficients for each lag k (in quarters), and evaluate the 25th, 50th and 75th percentile (in the table 25%, 50% and 75% respectively). For every k we also report the number \mathcal{N} of significant coefficients at the 5% level (if they exceed $2/\sqrt{T}$ in absolute value) amongst the 53, and the number of significantly positive (indicated by +) and negative (indicated by -) coefficients. In the table, significant coefficients at the 5% level are denoted by *. The sample is quarterly observation of 53 areas from 1994:2 to 2003:1.

Panel A: Excess Returns												
Apartments							Industrial					
k	25%	50%	75%	\mathcal{N}	+	-	25%	50%	75%	\mathcal{N}	+	-
1	-0.101	-0.007	0.170	5	4	1	-0.093	0.043	0.162	7	4	3
2	-0.171	-0.083	0.038	8	3	4	-0.186	-0.072	0.073	7	2	5
3	-0.121	-0.019	0.090	4	1	3	-0.109	-0.032	0.069	1	1	0
4	-0.063	0.029	0.149	1	1	0	-0.104	0.016	0.105	1	0	1
8	-0.128	0.032	0.150	1	1	0	-0.061	0.017	0.117	2	1	1
12	-0.117	-0.023	0.101	5	2	3	-0.078	-0.030	0.111	6	3	3
16	-0.100	-0.016	0.121	4	3	1	-0.107	-0.040	0.044	3	2	1
20	-0.172	-0.053	0.068	6	3	3	-0.057	0.057	0.146	9	5	4

Retail						Offices						
k	25%	50%	75%	\mathcal{N}	+	-	25%	50%	75%	\mathcal{N}	+	-
1	0.058	0.168	0.283	8	8	0	0.101	0.287	0.380*	25	24	1
2	-0.042	0.092	0.216	8	7	1	0.008	0.099	0.212	8	8	0
3	-0.058	0.054	0.196	2	1	1	-0.082	0.074	0.216	1	1	0
4	-0.086	-0.011	0.106	2	1	1	-0.102	-0.003	0.141	0	0	0
8	-0.267	-0.129	-0.050	4	0	4	-0.176	-0.072	0.021	5	0	5
12	-0.165	-0.104	0.015	5	2	3	-0.200	-0.018	0.070	6	0	6
16	-0.214	-0.109	0.052	3	1	2	-0.209	-0.110	-0.019	10	2	8
20	-0.064	0.142	0.361*	18	16	2	-0.056	0.078	0.197	12	9	3

Table 1 (Cont'd): Autocorrelation Coefficients of Excess Returns, Rent Growth, and Log Cap Rates

Panel B: Rent Growth												
<i>k</i>	Apartments						Industrial					
	25%	50%	75%	\mathcal{N}	+	-	25%	50%	75%	\mathcal{N}	+	-
1	-0.069	0.078	0.168	8	7	1	-0.090	0.049	0.204	10	6	4
2	-0.070	0.077	0.241	6	6	0	-0.099	0.049	0.173	4	3	1
3	-0.003	0.075	0.235	7	7	0	-0.016	0.081	0.187	6	6	0
4	0.016	0.128	0.228	6	5	1	-0.012	0.067	0.150	1	1	0
8	-0.117	0.028	0.135	3	0	3	-0.096	-0.004	0.132	3	1	2
12	-0.120	-0.020	0.167	9	8	1	-0.158	-0.055	0.121	5	1	4
16	-0.168	-0.048	0.064	5	1	4	-0.163	-0.078	0.029	4	1	3
20	-0.198	-0.008	0.115	5	0	5	-0.172	-0.053	0.096	5	0	5
<i>k</i>	Retail						Offices					
	25%	50%	75%	\mathcal{N}	+	-	25%	50%	75%	\mathcal{N}	+	-
1	-0.042	0.041	0.124	6	3	3	0.018	0.119	0.374*	17	14	3
2	-0.098	0.039	0.188	6	6	0	0.032	0.122	0.264	9	9	0
3	-0.082	0.042	0.192	4	3	1	-0.017	0.070	0.168	7	7	0
4	-0.069	0.013	0.173	1	1	0	-0.044	0.041	0.134	5	5	0
8	-0.130	-0.049	0.052	2	0	2	-0.099	-0.013	0.077	2	1	1
12	-0.130	-0.033	0.058	5	2	3	-0.136	-0.011	0.079	6	1	5
16	-0.108	-0.043	0.043	2	2	0	-0.217	-0.052	0.048	6	1	5
20	-0.090	-0.024	0.090	7	3	4	-0.210	-0.076	0.016	9	1	8

Table continued from previous page.

Table 1 (Cont'd): Autocorrelation Coefficients of Excess Returns, Rent Growth, and Log Cap Rates

Panel C: Log Cap Rates												
Apartments							Industrial					
k	25%	50%	75%	\mathcal{N}	+	-	25%	50%	75%	\mathcal{N}	+	-
1	0.723*	0.815*	0.861*	53	53	0	0.635*	0.744*	0.818*	52	52	0
2	0.469*	0.660*	0.740*	46	46	0	0.403*	0.517*	0.658*	43	43	0
3	0.363*	0.532*	0.652*	42	42	0	0.198	0.357*	0.495*	31	31	0
4	0.281	0.405*	0.545*	38	38	0	0.103	0.259	0.393*	21	21	0
8	-0.091	0.121	0.232	6	3	3	-0.111	0.008	0.129	4	1	3
12	-0.142	-0.029	0.048	1	0	1	-0.187	-0.110	0.004	2	0	2
16	-0.252	-0.138	-0.011	4	0	4	-0.278	-0.155	-0.054	4	0	4
20	-0.318	-0.226	-0.097	8	0	8	-0.277	-0.087	-0.037	9	0	9

Retail							Offices					
k	25%	50%	75%	\mathcal{N}	+	-	25%	50%	75%	\mathcal{N}	+	-
1	0.729*	0.834*	0.879*	52	52	0	0.782*	0.817*	0.880*	53	53	0
2	0.524*	0.657*	0.757*	50	50	0	0.535*	0.640*	0.759*	50	50	0
3	0.305	0.496*	0.646*	36	36	0	0.339	0.479*	0.636*	40	40	0
4	0.166	0.381*	0.533*	32	32	0	0.243	0.365*	0.500*	33	33	0
8	-0.118	0.029	0.142	5	3	2	-0.140	0.010	0.156	7	4	3
12	-0.265	-0.158	-0.039	7	0	7	-0.302	-0.190	-0.049	10	0	10
16	-0.333*	-0.223	-0.141	13	0	13	-0.348*	-0.234	-0.118	15	0	15
20	-0.280	-0.173	-0.070	6	0	6	-0.319	-0.184	-0.025	10	0	10

Table continued from previous page.

Table 2: Forecasting Regressions of Excess Returns on Log Cap Rate

The table reports the results from the pooled OLS overlapping regressions of excess returns between $t + 1$ and $t + k$ on the log cap rate at time t for apartments, industrial, retail, and office properties as it appears in equation (13). Excess returns over k periods are evaluated as sum of quarterly excess returns, including rents (total returns). The regression is performed by first stacking the observations for all areas in a given quarter and then for all quarters. In the table, k is the horizon of the forecasting regression (in quarters), β is the coefficient of the log cap rate, t_{NW} is the associated t-ratio using Newey-West standard errors, t/\sqrt{k} is the t-ratio suggested in Torous, Valkanov, and Yan (2005) to correct for the overlap, R^2 is the associated R^2 statistic and N is the number of observations involved in the pooled regression. The sample is quarterly observation of 53 areas from 1994:2 to 2003:1.

Apartments					Industrial				
k	β	t_{NW}	t/\sqrt{k}	R^2	β	t_{NW}	t/\sqrt{k}	R^2	N
1	0.078	6.823	7.717	0.032	0.118	6.588	8.406	0.038	1802
2	0.138	6.272	6.336	0.044	0.205	7.739	7.138	0.055	1749
3	0.201	6.098	6.059	0.061	0.286	8.040	6.689	0.073	1696
4	0.275	6.209	6.149	0.084	0.371	8.318	6.473	0.093	1643
8	0.532	5.946	5.328	0.137	0.640	7.388	5.025	0.124	1431
12	0.654	5.171	3.963	0.134	0.788	7.152	3.710	0.120	1272
16	0.800	5.295	3.273	0.146	0.946	6.534	3.046	0.129	1007
20	0.961	5.045	2.813	0.166	0.853	3.960	1.899	0.083	795
Retail					Offices				
k	β	t_{NW}	t/\sqrt{k}	R^2	β	t_{NW}	t/\sqrt{k}	R^2	N
1	0.090	7.184	8.500	0.039	0.052	5.096	5.028	0.014	1802
2	0.199	7.907	8.451	0.076	0.105	4.939	4.412	0.022	1749
3	0.307	7.708	8.084	0.104	0.156	4.590	3.955	0.027	1696
4	0.415	7.618	7.798	0.129	0.203	4.191	3.581	0.030	1643
8	0.833	7.770	7.083	0.219	0.346	2.934	2.543	0.035	1431
12	1.098	7.111	5.749	0.246	0.339	1.598	1.488	0.021	1272
16	1.074	5.628	3.970	0.201	0.191	0.677	0.577	0.005	1007
20	0.857	4.268	2.322	0.120	0.201	0.647	0.479	0.005	795

Table 3: Forecasting Regressions of Rent Growth on Log Cap Rate

The table reports the results from the pooled OLS overlapping regressions of dividend growth between $t + 1$ and $t + k$ on the log cap rate at time t for apartments, industrial, retail, and office properties as it appears in equation (14). The regression is performed by first stacking the observations for all areas in a given quarter and then for all quarters. In the table, k is the horizon of the forecasting regression, λ is the coefficient of the log cap rate, t_{NW} is the associated t-ratio using Newey-West standard errors, t/\sqrt{k} is the t-ratio suggested in Torous, Valkanov, and Yan (2005) to correct for the overlap, R^2 is the associated R^2 statistic and N is the number of observations involved in the pooled regression. The sample is quarterly observation of 53 areas between 1994:2 and 2003:1.

Apartments					Industrial				
k	λ	t_{NW}	t/\sqrt{k}	R^2	λ	t_{NW}	t/\sqrt{k}	R^2	N
1	0.024	2.828	3.145	0.005	0.013	0.875	1.144	0.001	1802
2	0.051	2.718	2.979	0.010	0.023	1.135	1.033	0.001	1749
3	0.078	2.557	2.824	0.014	0.046	1.591	1.359	0.003	1696
4	0.107	2.496	2.713	0.018	0.074	1.930	1.555	0.006	1643
8	0.207	2.388	2.196	0.026	0.218	2.852	1.914	0.020	1431
12	0.242	2.117	1.577	0.024	0.279	2.772	1.441	0.020	1272
16	0.285	2.174	1.255	0.024	0.425	3.180	1.470	0.033	1007
20	0.380	2.250	1.201	0.035	0.381	1.946	0.904	0.020	795
Retail					Offices				
k	λ	t_{NW}	t/\sqrt{k}	R^2	λ	t_{NW}	t/\sqrt{k}	R^2	N
1	0.010	0.916	1.022	0.001	-0.013	-1.323	-1.337	0.001	1802
2	0.011	0.513	0.520	0.000	-0.021	-1.085	-0.985	0.001	1749
3	0.043	1.304	1.313	0.003	-0.030	-0.927	-0.834	0.001	1696
4	0.075	1.601	1.637	0.006	-0.033	-0.713	-0.635	0.001	1643
8	0.263	2.540	2.413	0.032	-0.108	-0.897	-0.855	0.004	1431
12	0.385	2.665	2.128	0.043	-0.292	-1.360	-1.404	0.019	1272
16	0.369	2.087	1.428	0.031	-0.509	-1.747	-1.685	0.043	1007
20	0.184	1.044	0.525	0.007	-0.728	-2.190	-1.817	0.077	795

Table 4: Forecasting Regressions of Excess Returns on Log Cap Rate with Fixed Effect

The table reports the results from the pooled OLS overlapping regressions of excess returns between $t + 1$ and $t + k$ on the log cap rate at time t and on 53 cross-sectional dummies for apartments, industrial, retail, and office properties. The regression is performed by first regressing excess returns on 53 cross-sectional dummies, and then regressing the errors from this regression on the log cap rate. Excess returns over k periods are evaluated as sum of quarterly excess returns, including rents (total returns). In the table, k is the horizon of the forecasting regression (in quarters), β is the coefficient of the log cap rate, t_{NW} is the associated t-ratio using Newey-West standard errors, t/\sqrt{k} is the t-ratio suggested in Torous, Valkanov, and Yan (2005) to correct for the overlap, R^2 is the associated adjusted R^2 statistic and N is the number of observations involved in the pooled regression. The sample is quarterly observation of 53 areas between 1994:2 and 2003:1. The coefficients on the dummies are omitted.

Apartments					Industrial				
k	β	t_{NW}	t/\sqrt{k}	R^2	β	t_{NW}	t/\sqrt{k}	R^2	N
1	0.085	7.296	8.591	0.039	0.129	8.734	9.315	0.046	1802
2	0.151	7.052	7.129	0.055	0.223	9.089	7.979	0.068	1749
3	0.214	6.896	6.767	0.075	0.309	8.933	7.497	0.091	1696
4	0.287	7.182	6.859	0.103	0.399	9.073	7.329	0.116	1643
8	0.535	7.950	6.177	0.176	0.684	8.869	6.052	0.170	1431
12	0.616	6.665	4.738	0.181	0.827	9.456	4.786	0.184	1272
16	0.633	5.695	3.570	0.169	0.925	9.055	4.128	0.213	1007
20	0.588	5.651	2.682	0.154	0.725	5.752	2.703	0.156	795
Retail					Offices				
k	β	t_{NW}	t/\sqrt{k}	R^2	β	t_{NW}	t/\sqrt{k}	R^2	N
1	0.088	6.576	8.430	0.038	0.067	5.706	6.623	0.024	1802
2	0.188	7.468	8.304	0.073	0.134	5.836	5.860	0.038	1749
3	0.286	7.839	7.938	0.100	0.200	6.045	5.371	0.049	1696
4	0.383	8.314	7.690	0.126	0.264	6.064	5.007	0.058	1643
8	0.724	10.148	6.963	0.214	0.457	5.755	3.880	0.078	1431
12	0.891	10.066	5.607	0.237	0.479	4.566	2.799	0.072	1272
16	0.759	8.060	3.735	0.182	0.294	2.710	1.397	0.030	1007
20	0.365	3.998	1.711	0.069	0.089	0.982	0.445	0.005	795

Table 5: Forecasting Regressions of Excess Returns on Log Cap Rate with Fixed Effect from 1985

The table reports the results from the pooled OLS overlapping regressions of excess returns between $t + 1$ and $t + k$ on the log cap rate at time t and on 21 cross-sectional dummies for apartments, industrial, retail, and office properties from 1985 to 2002. The regression is performed by first regressing excess returns on 21 cross-sectional dummies, and then regressing the errors from this regression on the log cap rate. Excess returns over k periods are evaluated as sum of quarterly excess returns, including rents (total returns). In the table, k is the horizon of the forecasting regression (in quarters), β is the coefficient of the log cap rate, t_{NW} is the associated t-ratio using Newey-West standard errors, t/\sqrt{k} is the t-ratio suggested in Torous, Valkanov, and Yan (2005) to correct for the overlap, R^2 is the associated adjusted R^2 statistic and N is the number of observations involved in the regression. The sample is biannual observation of 21 areas between 1985:4 and 2002:4. The coefficients on the dummies are omitted.

Apartments					Industrial				
k	β	t_{NW}	t/\sqrt{k}	R^2	β	t_{NW}	t/\sqrt{k}	R^2	N
4	0.261	4.768	4.499	0.057	0.392	5.378	5.355	0.079	672
8	0.606	5.511	4.792	0.128	0.775	5.624	4.874	0.131	630
12	1.023	6.276	5.205	0.217	1.247	5.917	4.949	0.201	588
16	1.470	6.853	5.521	0.310	1.747	7.041	5.089	0.276	546
20	1.768	7.295	5.280	0.357	2.083	8.354	4.828	0.317	504
Retail					Offices				
k	β	t_{NW}	t/\sqrt{k}	R^2	β	t_{NW}	t/\sqrt{k}	R^2	N
4	0.376	6.877	6.962	0.126	0.278	5.598	6.261	0.105	672
8	0.793	7.143	6.526	0.213	0.593	5.613	5.692	0.171	630
12	1.175	7.382	6.036	0.272	0.908	6.319	5.345	0.226	588
16	1.469	7.379	5.459	0.305	1.159	6.996	4.804	0.253	546
20	1.649	7.530	4.808	0.315	1.326	6.718	4.217	0.262	504

Table 6: Forecasting Regressions of Excess Returns on Log Cap Rate and Economic Variables

The table reports the results from the pooled OLS overlapping regressions of excess returns between $t + 1$ and $t + k$ on the log cap rate and economic variables at time t for apartments, industrial, retail and offices. The results refer to a 4-year horizon. The table shows three specifications for each real estate property type: (1) including the log cap rate and the difference in log of the economic variables, (2) including the log cap rate, the difference in log of the economic variables, the level of the economic variables lagged twice and the coastal dummy, (3) including the difference in log of the economic variables, the level of the economic variables twice lagged and the coastal dummy. The variables are defined as follows: *cap* is the log cap rate at time t , *gpop*, *gemp*, *ginc* and *gcc* are growth in population, employment, per capita income and construction costs at time t respectively, *pop*, *emp*, *inc* and *cc* are the levels of the variables at time $t - 2$ and *coast* is the coastal dummy. The t -ratios, in parentheses, are evaluated as t/\sqrt{k} as suggested in Torous, Valkanov, and Yan (2005) to correct for the overlap. The sample is annual observations of 53 areas between 1994 and 2001.

	Apartments			Industrial			Retail			Offices		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
cap	1.026 (3.332)	1.132 (4.044)	-	1.044 (2.929)	1.247 (3.786)	-	1.303 (4.971)	1.375 (5.080)	-	0.173 (0.509)	0.652 (1.888)	-
gpop	1.758 (0.736)	3.348 (1.488)	0.937 (0.386)	0.136 (0.072)	1.488 (0.812)	0.385 (0.192)	3.390 (2.188)	4.122 (2.580)	2.372 (1.285)	-0.896 (-0.283)	1.112 (0.367)	0.521 (0.169)
gemp	-1.422 (-0.756)	-0.816 (-0.450)	-0.768 (-0.379)	0.738 (0.478)	1.104 (0.730)	0.835 (0.500)	0.220 (0.175)	-0.034 (-0.026)	0.431 (0.280)	0.678 (0.261)	1.055 (0.420)	1.013 (0.393)
ginc	-0.248 (-0.210)	-0.845 (-0.717)	-1.897 (-1.475)	-1.107 (-1.145)	-1.093 (-1.108)	-1.971 (-1.860)	-0.454 (-0.590)	-0.029 (-0.035)	-0.673 (-0.688)	0.009 (0.006)	-1.350 (-0.843)	-1.074 (-0.657)
gcc	-0.095 (-0.073)	0.209 (0.177)	0.937 (0.717)	0.366 (0.345)	0.532 (0.545)	0.807 (0.751)	0.627 (0.733)	0.720 (0.856)	1.030 (1.036)	-1.026 (-0.579)	-0.101 (-0.062)	-0.236 (-0.142)
pop	-	-0.039 (-0.283)	-0.003 (-0.017)	-	0.110 (0.959)	0.125 (0.989)	-	0.074 (0.751)	0.102 (0.874)	-	-0.443 (-2.194)	-0.315 (-1.614)
emp	-	0.105 (0.750)	0.061 (0.390)	-	-0.057 (-0.488)	-0.079 (-0.615)	-	-0.039 (-0.382)	-0.077 (-0.647)	-	0.490 (2.337)	0.340 (1.707)
pcinc	-	-0.045 (-0.605)	-0.062 (-0.749)	-	0.014 (0.217)	-0.001 (-0.015)	-	-0.016 (-0.293)	-0.053 (-0.840)	-	-0.192 (-1.849)	-0.172 (-1.621)
cc	-	0.198 (1.549)	0.160 (1.120)	-	0.078 (0.733)	0.067 (0.572)	-	-0.087 (-0.941)	-0.134 (-1.234)	-	0.358 (2.002)	0.306 (1.685)
coast	-	0.055 (1.785)	0.064 (1.861)	-	0.043 (1.661)	0.033 (1.181)	-	0.032 (1.438)	0.017 (0.639)	-	0.112 (2.632)	0.106 (2.443)
R_{adj}^2	0.190	0.352	0.188	0.159	0.309	0.156	0.383	0.421	0.189	-0.009	0.183	0.140

Table 7: Forecasting Regressions of Rent Growth on Log Cap Rate and Economic Variables

The table reports the results from the pooled OLS overlapping regressions of rent growth between $t + 1$ and $t + k$ on the log cap rate and economic variables at time t for apartments, industrial, retail, and office properties. The results refer to a 4-year horizon. The table shows three specifications for each real estate property type: (1) including the log cap rate and the difference in log of the economic variables, (2) including the log cap rate, the difference in log of the economic variables, the level of the economic variables lagged twice and the coastal dummy, (3) including the difference in log of the economic variables, the level of the economic variables twice lagged and the coastal dummy. The variables are defined as follows: *cap* is the log cap rate at time t , *gpop*, *gemp*, *ginc* and *gcc* are growth in population, employment, per capita income and construction costs at time t respectively, *pop*, *emp*, *inc* and *cc* are the levels of the variables at time $t - 2$ and *coast* is the coastal dummy. The t -ratios, in parentheses, are evaluated as t/\sqrt{k} as suggested in Torous, Valkanov, and Yan (2005) to correct for the overlap. The sample is annual observations of 53 areas between 1994 and 2001.

	Apartments			Industrial			Retail			Offices		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
cap	0.261 (0.919)	0.329 (1.200)	-	0.380 (1.141)	0.537 (1.689)	-	0.468 (1.826)	0.503 (1.902)	-	-0.590 (-1.924)	-0.242 (-0.747)	-
gpop	0.150 (0.068)	1.354 (0.615)	0.654 (0.305)	-0.718 (-0.404)	0.293 (0.165)	-0.183 (-0.102)	3.111 (2.053)	3.780 (2.422)	3.140 (2.008)	-1.355 (-0.475)	-0.050 (-0.018)	0.169 (0.060)
gemp	-0.153 (-0.088)	0.111 (0.063)	0.125 (0.070)	1.116 (0.773)	1.405 (0.961)	1.289 (0.865)	-0.003 (-0.002)	-0.335 (-0.263)	-0.165 (-0.126)	0.968 (0.413)	1.249 (0.531)	1.264 (0.536)
ginc	-1.858 (-1.710)	-2.102 (-1.822)	-2.408 (-2.120)	-1.679 (-1.858)	-1.610 (-1.689)	-1.988 (-2.104)	-1.203 (-1.599)	-0.830 (-1.016)	-1.066 (-1.286)	-0.954 (-0.685)	-1.962 (-1.310)	-2.064 (-1.380)
gcc	0.238 (0.199)	0.419 (0.362)	0.630 (0.546)	0.277 (0.279)	0.385 (0.409)	0.504 (0.525)	0.356 (0.425)	0.493 (0.599)	0.606 (0.720)	-0.520 (-0.326)	0.187 (0.124)	0.237 (0.156)
pop	-	0.036 (0.266)	0.046 (0.342)	-	0.089 (0.807)	0.096 (0.850)	-	0.022 (0.233)	0.033 (0.330)	-	-0.377 (-2.000)	-0.425 (-2.384)
emp	-	0.008 (0.057)	-0.005 (-0.037)	-	-0.042 (-0.370)	-0.051 (-0.446)	-	0.013 (0.134)	-0.001 (-0.009)	-	0.408 (2.077)	0.464 (2.547)
pcinc	-	-0.024 (-0.335)	-0.030 (-0.400)	-	0.012 (0.206)	0.006 (0.100)	-	-0.048 (-0.911)	-0.062 (-1.151)	-	-0.147 (-1.514)	-0.155 (-1.596)
cc	-	0.137 (1.096)	0.126 (1.001)	-	0.025 (0.243)	0.020 (0.195)	-	-0.083 (-0.925)	-0.100 (-1.093)	-	0.225 (1.346)	0.245 (1.477)
coast	-	0.030 (0.994)	0.032 (1.074)	-	0.035 (1.395)	0.031 (1.215)	-	0.033 (1.525)	0.027 (1.246)	-	0.092 (2.314)	0.094 (2.366)
R_{adj}^2	0.075	0.164	0.149	0.078	0.190	0.157	0.225	0.275	0.237	0.040	0.162	0.158

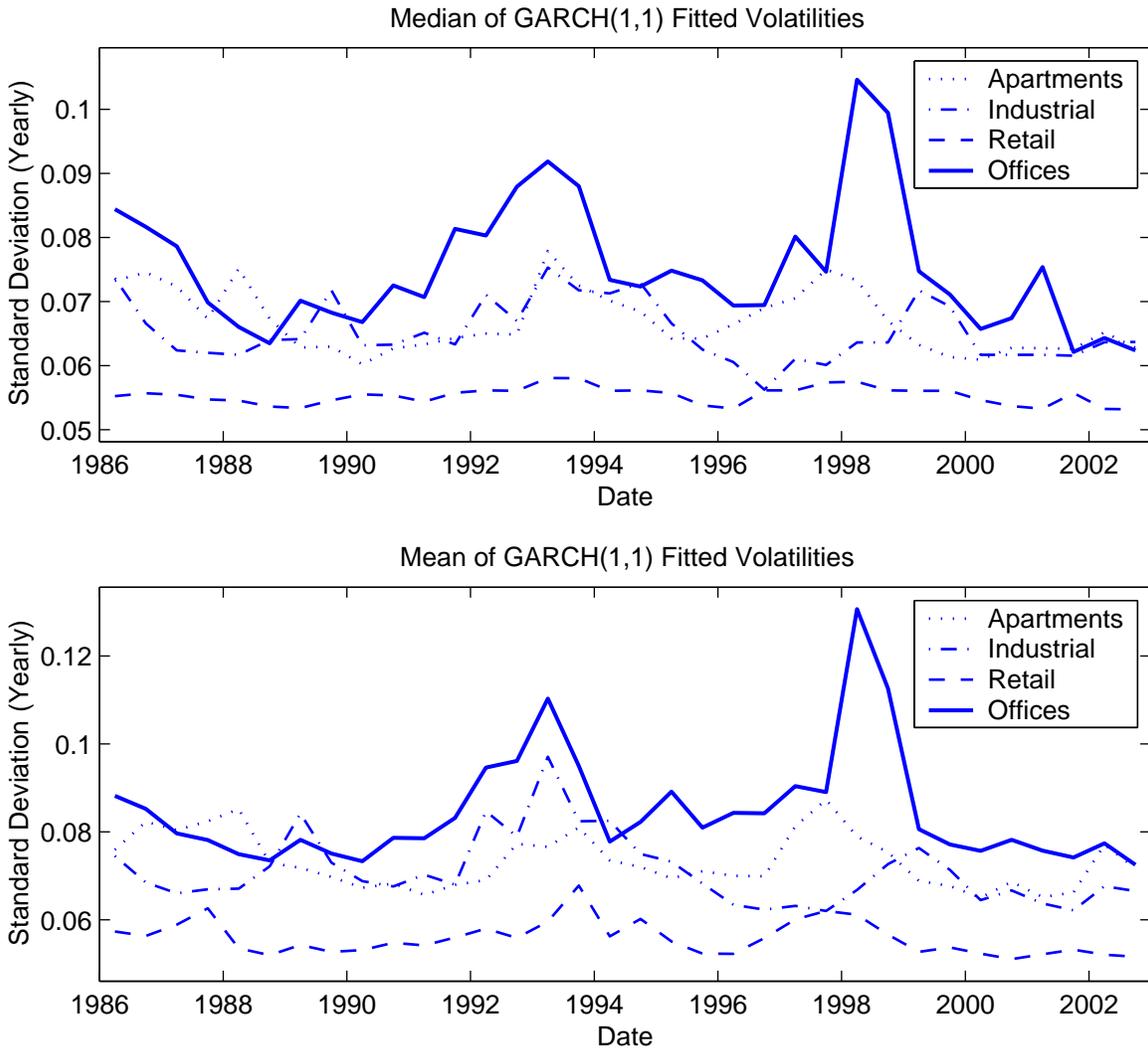
Table 8: Regressions of Future Excess Returns and Rent Growth on Economic Variables from 1985

The table reports the results of the pooled OLS regression of 1-year ahead excess returns and rent growth on economic variables. *TSPR* is the difference between the yield on 10-year and 1-year Treasuries, *DSPR* is the difference between the yield on BAA and AAA rated corporate bonds, *CPIRET* is inflation computed as the growth of the CPI index, and *TB3M* is the three-months Treasury bill rate. The *t*-ratios, in parentheses, are evaluated as t/\sqrt{k} as suggested in Torous, Valkanov, and Yan (2005) to correct for the overlap. The sample is biannual observations from 1985:4 to 2002:4.

Panel A: Future Excess Returns				
	Apartments	Industrial	Retail	Offices
TSPR	0.545 (0.875)	0.083 (0.145)	-0.321 (-0.807)	-0.454 (-0.727)
DSPR	-10.645 (-4.182)	-4.241 (-1.807)	-3.031 (-1.864)	-8.413 (-3.300)
CPIRET	-0.736 (-1.703)	-0.946 (-2.374)	-0.958 (-3.471)	-1.479 (-3.417)
TB3M	-1.150 (-2.012)	-0.737 (-1.398)	-1.315 (-3.599)	-1.417 (-2.474)
R^2	0.200	0.101	0.243	0.234
Panel B: Future Rent Growth				
	Apartments	Industrial	Retail	Offices
TSPR	0.894 (2.046)	0.475 (1.121)	0.467 (1.421)	0.354 (0.668)
DSPR	-6.739 (-3.772)	-4.084 (-2.360)	-4.116 (-3.068)	-9.236 (-4.271)
CPIRET	-0.498 (-1.642)	-0.704 (-2.395)	-0.530 (-2.325)	-1.235 (-3.363)
TB3M	0.401 (1.000)	0.397 (1.021)	0.215 (0.714)	0.327 (0.674)
R^2	0.069	0.042	0.066	0.135

Figure 1: Volatilities of Rent Growth

The figure reports the median (top panel) and mean (bottom panel) cross-sectional yearly volatilities of the portion of rent growth that is orthogonal to economic fluctuations, fitted from a GARCH(1,1) model. To construct these series, we first regress the rent growth rates of each property type and each metropolitan area on the term spread, default, spread, inflation, and the 3-months Treasury bill rate as in Table (8). Using the residuals from these regressions, we estimate a GARCH(1,1) model for each of the fifty-three time series of rent growth for every property type. We then compute for a given property type the median and mean fitted volatilities across the metropolitan areas in each period. Results from offices are marked by a solid line. The sample is biannual observations from 1985 : 4 to 2002 : 4.



Appendix 1 - Metropolitan Areas

This table contains a description and summary statistics of the data used in the empirical section. The table reports the State, the Metropolitan area as well as averages of annualized excess returns (denoted by r), annualized dividend growth (denoted by g) and annual cap rates (denoted by cap), for apartments (superscript apt), industrial (superscript ind), retail (superscript rtl) and offices (superscript off). The sample is quarterly observation of 53 areas between 1994:2 and 2003:1. The average annual three-month Treasury bill rate during the period was 0.045.

State	Metropolitan area	r^{apt}	r^{ind}	r^{rtl}	r^{off}	g^{apt}	g^{ind}	g^{rtl}	g^{off}	cap^{apt}	cap^{ind}	cap^{rtl}	cap^{off}	
Alabama	1 . Birmingham - MSA	0.072	0.063	0.077	0.067	0.022	0.010	0.018	0.020	0.089	0.093	0.097	0.094	
Arizona	2 . Phoenix - MSA	0.107	0.089	0.120	0.080	0.054	0.034	0.056	0.030	0.084	0.085	0.092	0.092	
California	3 . Orange County - PMSA	0.116	0.079	0.075	0.089	0.053	0.023	0.018	0.033	0.087	0.087	0.091	0.084	
	4 . Sacramento - CMSA	0.104	0.084	0.071	0.077	0.046	0.024	0.023	0.032	0.091	0.093	0.092	0.083	
	5 . Los Angeles - PMSA	0.139	0.120	0.083	0.064	0.066	0.046	0.019	0.009	0.084	0.089	0.094	0.083	
	6 . Oakland-East Bay - PMSA	0.101	0.084	0.076	0.058	0.037	0.032	0.021	0.010	0.087	0.092	0.091	0.090	
	7 . San Diego - MSA	0.129	0.084	0.080	0.114	0.058	0.034	0.020	0.046	0.082	0.093	0.092	0.085	
	8 . Riverside-S. Bernardino - PMSA	0.129	0.115	0.078	0.084	0.072	0.038	0.016	0.024	0.089	0.090	0.090	0.096	
	9 . San Jose - PMSA	0.104	0.096	0.064	0.121	0.033	0.043	0.011	0.062	0.082	0.089	0.095	0.092	
	10 . San Francisco - PMSA	0.103	0.082	0.054	0.134	0.040	0.024	0.008	0.085	0.085	0.091	0.089	0.085	
	Colorado	11 . Denver - CMSA	0.115	0.099	0.108	0.099	0.042	0.040	0.055	0.045	0.085	0.090	0.092	0.084
	Connecticut	12 . Hartford - MSA	0.080	0.043	0.063	0.062	0.029	-0.012	0.006	0.008	0.091	0.096	0.096	0.098
D.C.	13 . Washington - MSA	0.109	0.097	0.081	0.103	0.033	0.036	0.027	0.049	0.089	0.093	0.090	0.081	
Florida	14 . Fort Lauderdale - PMSA	0.090	0.082	0.098	0.072	0.034	0.033	0.033	0.020	0.087	0.093	0.092	0.093	
	15 . Jacksonville - MSA	0.092	0.076	0.087	0.078	0.053	0.015	0.033	0.016	0.089	0.090	0.094	0.099	
	16 . Miami - PMSA	0.075	0.084	0.066	0.064	0.023	0.037	0.014	0.044	0.087	0.089	0.090	0.088	
	17 . Orlando - MSA	0.080	0.086	0.094	0.070	0.023	0.039	0.030	0.028	0.089	0.094	0.091	0.089	
	18 . West Palm Beach - MSA	0.089	0.090	0.079	0.078	0.035	0.034	0.035	0.032	0.086	0.090	0.090	0.091	
	19 . Tampa-St. Petersburg - MSA	0.090	0.084	0.091	0.079	0.030	0.028	0.034	0.028	0.090	0.094	0.094	0.093	
Georgia	20 . Atlanta - MSA	0.085	0.082	0.065	0.056	0.031	0.017	0.022	0.026	0.082	0.090	0.090	0.090	

Appendix 1 - Metropolitan Areas (cont'd)

State	Metropolitan area	r^{apt}	r^{ind}	r^{rtl}	r^{off}	g^{apt}	g^{ind}	g^{rtl}	g^{off}	cap^{apt}	cap^{ind}	cap^{rtl}	cap^{off}
Illinois	21 . Chicago - PMSA	0.082	0.071	0.074	0.098	0.025	0.013	0.026	0.026	0.087	0.091	0.091	0.087
Indiana	22 . Indianapolis - MSA	0.083	0.052	0.056	0.053	0.035	0.004	0.003	0.008	0.090	0.093	0.095	0.091
Louisiana	23 . New Orleans - MSA	0.111	0.054	0.073	0.098	0.041	0.002	0.016	0.034	0.097	0.094	0.096	0.100
Maryland	24 . Baltimore - PMSA	0.093	0.071	0.066	0.087	0.029	0.019	0.019	0.047	0.090	0.092	0.094	0.091
Massachusetts	25 . Boston - PMSA	0.131	0.091	0.051	0.100	0.078	0.034	0.011	0.061	0.092	0.092	0.090	0.082
Michigan	26 . Detroit - PMSA	0.081	0.081	0.060	0.037	0.026	0.030	0.009	0.000	0.089	0.095	0.094	0.091
Minnesota	27 . Minneapolis-St. Paul - MSA	0.101	0.083	0.062	0.084	0.050	0.029	0.009	0.037	0.086	0.095	0.094	0.092
Missouri	28 . Kansas City - MSA	0.083	0.064	0.085	0.055	0.039	0.013	0.034	0.012	0.086	0.094	0.095	0.089
	29 . St. Louis - MSA	0.092	0.089	0.081	0.038	0.032	0.037	0.028	-0.002	0.089	0.091	0.095	0.091
Nevada	30 . Las Vegas - MSA	0.064	0.084	0.089	0.056	0.027	0.019	0.041	0.008	0.086	0.088	0.092	0.093
New Jersey	31 . Central New Jersey -PMSAs	0.102	0.081	0.066	0.111	0.042	0.028	0.013	0.050	0.089	0.092	0.089	0.090
	32 . Northern New Jersey -PMSAs	0.113	0.086	0.064	0.056	0.052	0.030	0.013	-0.005	0.093	0.092	0.089	0.096
New York	33 . Nassau-Suffolk - PMSA	0.116	0.080	0.066	0.078	0.058	0.025	0.010	0.014	0.093	0.090	0.092	0.088
North Carolina	34 . Charlotte - MSA	0.085	0.058	0.063	0.055	0.035	0.003	0.009	0.008	0.088	0.091	0.093	0.088
	35 . Raleigh-Durham - MSA	0.064	0.064	0.074	0.064	0.011	0.011	0.018	0.014	0.083	0.091	0.090	0.086
	36 . Greensboro- Winston-Salem - High Point - MSA	0.061	0.054	0.072	0.055	0.020	0.008	0.021	0.006	0.091	0.094	0.096	0.095
Ohio	37 . Cincinnati - CMSA	0.086	0.070	0.055	0.047	0.040	0.028	0.004	0.005	0.094	0.090	0.093	0.090
	38 . Cleveland - CMSA	0.074	0.085	0.066	0.062	0.007	0.025	0.016	0.007	0.095	0.096	0.095	0.092
	39 . Columbus - MSA	0.073	0.061	0.047	0.025	0.023	0.006	-0.002	-0.012	0.090	0.092	0.091	0.092
Oklahoma	40 . Oklahoma City - MSA	0.111	0.086	0.108	0.086	0.044	0.036	0.042	0.021	0.097	0.095	0.094	0.097
Oregon	41 . Portland - PMSA	0.089	0.091	0.097	0.088	0.024	0.036	0.034	0.033	0.088	0.092	0.093	0.085
Pennsylvania	42 . Philadelphia - PMSA	0.095	0.065	0.063	0.060	0.036	0.014	0.003	0.009	0.091	0.093	0.094	0.094
	43 . Pittsburgh - MSA	0.062	0.069	0.049	0.048	0.005	0.015	-0.005	0.002	0.096	0.096	0.098	0.094

Appendix 1 - Metropolitan Areas (cont'd)

State	Metropolitan area	r^{apt}	r^{ind}	r^{rtl}	r^{off}	g^{apt}	g^{ind}	g^{rtl}	g^{off}	cap^{apt}	cap^{ind}	cap^{rtl}	cap^{off}
Tennessee	44 . Memphis - MSA	0.093	0.054	0.067	0.054	0.037	0.011	0.015	0.008	0.085	0.088	0.095	0.092
	45 . Nashville - MSA	0.110	0.073	0.080	0.043	0.027	0.026	0.025	0.006	0.089	0.091	0.094	0.092
Texas	46 . Austin - MSA	0.107	0.059	0.100	0.080	0.037	0.011	0.050	0.028	0.084	0.092	0.091	0.090
	47 . Dallas-Ft. Worth - CMSA	0.105	0.079	0.095	0.073	0.052	0.024	0.032	0.020	0.085	0.090	0.090	0.089
	48 . Houston - PMSA	0.120	0.093	0.115	0.103	0.049	0.049	0.045	0.046	0.087	0.089	0.095	0.096
	49 . San Antonio - MSA	0.112	0.090	0.075	0.064	0.036	0.041	0.023	0.020	0.090	0.093	0.093	0.093
Utah	50 . Salt Lake City - MSA	0.065	0.055	0.081	0.069	0.025	0.005	0.024	0.024	0.091	0.093	0.089	0.088
Virginia	51 . Norfolk - MSA	0.093	0.055	0.062	0.072	0.041	0.001	0.009	0.022	0.089	0.096	0.091	0.096
Washington	52 . Seattle - PMSA	0.121	0.064	0.069	0.086	0.038	0.018	0.026	0.045	0.084	0.086	0.090	0.085
Wisconsin	53 . Milwaukee - PMSA	0.068	0.090	0.056	0.054	0.012	0.037	0.007	0.000	0.095	0.093	0.094	0.091
<i>National Average</i>		0.104	0.082	0.072	0.091	0.039	0.023	0.017	0.027	0.087	0.091	0.092	0.087