

Expected Returns and Expected Growth in Rents of Commercial Real Estate¹

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Abstract

Commercial real estate expected returns and expected rent growth rates are time-varying. Relying on transactions data from a cross-section of U.S. metropolitan areas, we find that up to 30% of the variability of realized returns to commercial real estate can be accounted for by expected return variability, while expected rent growth rate variability explains up to 45% of the variability of realized rent growth rates. The cap rate, that is, the rent-price ratio in commercial real estate, captures fluctuations in expected returns for apartments, retail, as well as industrial properties. For offices, by contrast, cap rates do not forecast (in-sample) returns even though expected returns on offices are also time-varying. As implied by the present value relation, cap rates marginally forecast office rent growth but not rent growth of apartments, retail and industrial properties. We link these differences in in-sample predictability to differences in the stochastic properties of the underlying commercial real estate data generating processes. Also, rent growth predictability is mostly observed in locations characterized by higher population density and stringent land use restrictions. The opposite is true for return predictability. The dynamic portfolio implications of time-varying commercial real estate returns are also explored in the context of a portfolio manager investing in the aggregate stock market, Treasury bills as well as commercial real estate.

1 Introduction

U.S. commercial real estate prices fluctuate considerably, both cross-sectionally as well as over time. For example, the return to apartment buildings 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 percent 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 an important research question as commercial real estate represents a substantial fraction of total U.S. wealth. For example, Standard and Poor's estimates the value in 2007 of all U.S. commercial real estate to be about \$5.3 trillion, about one fifth of the stock market's value.

From an asset pricing perspective, the price of a commercial property, be it an office building, apartment, retail or industrial space, equals the present value of its future rents. This fundamental present value relation implies that observed fluctuations in commercial real estate prices should reflect variation in future rents, or in future discount rates, or both. The possibility of time-varying discount rates and rent growth rates should be explicitly considered in the valuation of commercial real estate as it is often conjectured that both fluctuate with the prevailing state of the economy. Case (2000), for example, 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 example of cyclical fluctuations in expected returns and rent growth rates that give rise to sizable variation in commercial real estate values. 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 dynamics of commercial real estate returns and rent growth rates.

In this paper, we investigate whether expected returns and expected growth in rents of commercial real estate are time-varying by relying on a version of Campbell and Shiller's (1988b) "dynamic Gordon" model. An implication of this model is that the cap rate, defined as the ratio between a property's rent and its price, should reflect fluctuations in expected returns, or in rent growth rates, or both. 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 rent plays the role of the dividend. By way of example, suppose that the cap rate for apartment buildings in Portland is

higher than the cap rate of similar properties in Dallas. The dynamic Gordon model implies that either future discount rates in Portland will be higher than those expected in Dallas, or that future rents in Portland are expected to grow at a slower rate than in Dallas, or both.

Commercial real estate offers a number of advantages over common stock when investigating the dynamics of expected returns and the growth in cash payouts. For example, it is often argued that common stock dividends do not accurately reflect the changing investment opportunities confronting a firm. Dividends are paid at the discretion of the firm's management and there is extensive evidence that they are either actively smoothed, the product of managers catering to particular clienteles, or the result of management's reaction to perceived mispricing (Shefrin and Statman (1984), Stein (1996), and Baker and Wurgler (2004)). By contrast, rents on commercial properties are not discretionary and are paid by tenants as opposed to property managers. Furthermore, commercial rents are particularly sensitive to prevailing economic conditions such as employment and growth in industrial production (DiPasquale and Wheaton (1996)).

In conducting our empirical analysis, we rely on a novel data set summarizing commercial real estate transactions across fifty-three U.S. metropolitan areas reported at a quarterly frequency over a sample period extending from the second quarter of 1994 to the first quarter of 2003. For a subset of twenty-one of these areas, we also have bi-annual observations beginning in the last quarter of 1985. These data are available for a variety of property types including offices, apartments, as well as retail and industrial properties. The transactions nature of our commercial real estate data differentiates it from the appraisal data typically relied upon in other studies. For example, unlike the serially correlated returns and rent growth rates characterizing appraisal data (Case and Shiller (1989, 1990)), returns and rent growth rates in our data are not serially correlated beyond a yearly horizon.

We find that higher cap rates predict higher future returns of apartment buildings as well as retail and industrial properties. Cap rates, however, do not predict the future returns of office buildings. For apartments, retail, and industrial properties, the predictability of returns is robust to controlling for cross-sectional differences using variables that capture regional variation in demographic, geographic, and various economic factors. In terms of the economic significance of this relation, 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 common

stock (Cochrane (2008)). The evidence of return predictability is primarily drawn from locations characterized by lower population density and less land use restrictions. By contrast, we do not find reliable evidence that cap rate fluctuations are associated with future movements in rent growth rates. Only for offices do we find some evidence of higher cap rates predicting lower future rent growth rates and then only at long horizons. Also, rent growth predictability is more likely to be observed in locations characterized by higher population density and stricter land use restrictions. These findings, however, should only be interpreted as in-sample evidence because our estimation procedure relies on data drawn from the entire sample period. Therefore, our results are not predictive in the sense that an investor in real-time would have been able to replicate them or profit from them (Goyal and Welch (2008)).

Taken together, our findings point to a fundamental difference between apartments, retail and industrial properties, where cap rates do forecast returns, versus office buildings, where they do not. This difference provides us with a unique opportunity to investigate under what circumstances valuation ratios of broadly similar assets –commercial real estate properties– can or cannot predict returns and the growth in cash payouts. To do so, we formulate an underlying structural model for returns and rent growth whose conditional expectations vary over time. An important feature of the model is that it captures the co-movement between the time-varying components of expected returns and expected rent growth ((Menzly, Santos, and Veronesi (2004), Lettau and Van Nieuwerburgh (2008), and Kojen and Van Binsbergen (2009)). Such a co-movement is not only supported by our data but, as we demonstrate, also generates systematic patterns in the coefficients of predictive regressions. Relying on an identification scheme which makes use of the estimated predictive regression coefficients as well as other moments of the data, we explicitly relate the predictive regression coefficients to the stochastic properties of returns and rent growth. By doing so, we are able to explain observed differences in the forecasting ability of cap rates across property types in terms of the underlying data generating processes.

The ability of the cap rate to forecast returns or rent growth depends primarily on two factors: the co-movement between expected returns and expected rent growth, and the extent to which variation in expected rent growth is orthogonal to the time-varying component of expected returns. Interestingly, the co-movement factor has a non-monotonic effect on the predictive regressions' slope coefficients. This reflects the fact that a greater co-movement reduces both the variability of the cap rate as well as its covariance with future returns. Variation in expected rent growth

orthogonal to the time-varying component of expected returns represents noise in the cap rate's ability to forecast returns. If cap rates are driven primarily by this orthogonal component then the cap rate's ability to forecast returns will be reduced while, at the same time, its ability to forecast rent growth will be improved. Because the cap rate is correlated with both expected returns and expected rent growth, this predictor is "imperfect" as in Pastor and Stambaugh (2009). However, unlike their reduced-form setup where expected returns are imperfectly correlated with a predictor, we follow Lettau and Van Nieuwerburgh (2008) and explicitly link the structural parameters of the data generating process to the coefficients of the predictive regression.

We find that offices are characterized by the largest co-movement between expected returns and expected rent growth and also have a relatively large noise component when compared to the other property types. These two features imply that office cap rates are an imperfect and extremely noisy proxy of future returns. This lack of predictability, however, does not mean that the expected return to offices is not time varying. To the contrary, we document that commercial real estate expected returns and expected rent growth are extremely volatile across all property types. In particular, the variability of realized returns accounted for by the variability of expected returns over the 1985 to 2002 sample period range from approximately 16% in the case of industrial properties to almost 30% in the case of retail properties. For rent growth rates over this same sample period, approximately 22% of the variability of realized industrial rent growth rates is explained by the variability of expected industrial rent growth rates, while, at the other extreme, expected office rent growth rates explain almost 43% of the variability of realized office rent growth rates.

Our empirical methodology differs in a number of ways from the standard approach of estimating predictive regressions by ordinary least squares (OLS). In particular, we rely on a generalized method of moments (GMM) procedure in which the present value constraint is imposed to jointly estimate the returns and rent growth predictive regressions. This restriction renders the system internally consistent as these regressions are explicitly related by the Campbell and Shiller (1988b) log-linearization. The predictive relations at all horizons are then estimated simultaneously as a system as opposed to horizon by horizon. We also use the entire cross-section of metropolitan areas when estimating the system for each commercial property type. Combining cross-sectional and time-series information improves the efficiency with which the predictive relations will be estimated. Finally, we rely on a double-resampling procedure to take into account the overlapping and cross-sectional nature of our data.

The view of commercial real estate that emerges from our analysis is that of an asset class characterized by fluctuations in expected returns not unlike that of common stock. This being the case, a natural question to ask is whether, like common stock, the allocation of commercial real estate within a portfolio can be improved by exploiting the time variation of its expected return. To do so, we use the parametric portfolio approach of Brandt and Santa-Clara (2006) to investigate the properties of a dynamic portfolio strategy in which funds are allocated between Treasury bills, common stock, and commercial real estate by taking advantage of the information provided by the dividend-price ratio as well as the cap rate. Including the cap rate in addition to the dividend yield has a significant impact on the dynamic asset allocation. In particular, the resultant dynamic portfolio strategy results in an increase of the Sharpe ratio from approximately 0.5 to almost 1.0 in comparison to the corresponding static portfolio position (which ignores predictability) and yields a certainty equivalent return of over 6 percent per year.

The plan of this paper is as follows. In Section 2, we present our commercial real estate valuation framework and the corresponding predictive regressions used to investigate the dynamics of commercial real estate returns and rent growth. The time-series and cross-sectional properties of our transactions-based commercial real estate data are also presented. These properties motivate an underlying structural model of the commercial real estate data generating process. The predictive regression coefficients can then be interpreted in terms of the properties of commercial real estate returns and rent growth implied by the structural model. Section 3 details a two-step estimation procedure which takes advantage of the pooled nature of our data to efficiently estimate predictive regressions. The results of estimating in-sample the predictive regressions and the corresponding structural parameters are then presented. In section 4, we investigate cross-sectional differences in our predictive regression results based on population density and land use regulation. We also test the robustness of our results to the inclusion of other cross-sectional determinants of commercial real estate returns and rent growth across metropolitan areas. Section 5 investigates the properties of a dynamic portfolio strategy which exploits the predictability of commercial real estate returns as well as the predictability of common stock returns. We offer concluding remarks in Section 6.

2 Commercial Real Estate Returns and Rents

2.1 The Cap Rate Model

We denote by $P_{i,t}^m$ the price of a commercial property in area i at the end of period t where the superscript m refers to the type of property being considered: apartments, office buildings, industrial, or retail properties.¹ Similarly, $H_{i,t+1}^m$ is the net rent² of a commercial property of type m in area i from period t to $t+1$. The gross return from holding a given commercial property from t to $t+1$ is defined by:

$$1 + R_{i,t+1}^m \equiv \frac{P_{i,t+1}^m + H_{i,t+1}^m}{P_{i,t}^m}. \quad (1)$$

The definition of the return to commercial real estate is similar to that of common stock. The only difference is that a commercial property pays rental income instead of a dividend. The rent-to-price ratio $H_{i,t}^m/P_{i,t}^m$, known as the cap rate in the commercial real estate industry (Geltner and Miller (2000), Brueggeman and Fisher (2008)), corresponds to the dividend-price ratio for stocks.

We define the log price, log return, log rent, and log rent-to-price ratio as $p_{i,t}^m \equiv \log(P_{i,t}^m)$, $r_{i,t+1}^m \equiv \log(1 + R_{i,t+1}^m)$, $h_{i,t+1}^m \equiv \log(H_{i,t+1}^m)$, and $cap_{i,t}^m \equiv h_{i,t}^m - p_{i,t}^m$, respectively. We follow Campbell and Shiller (1988b) and express $r_{i,t+1}^m$ using a first-order Taylor approximation as $r_{i,t+1}^m \approx \kappa + \rho p_{i,t+1}^m + (1-\rho)h_{i,t+1}^m - p_{i,t}^m$, where κ and ρ are parameters derived from the linearization.³ Solving this relation forward, imposing the transversality condition $\lim_{k \rightarrow \infty} \rho^k p_{i,t+k}^m = 0$ to avoid the presence of rational bubbles, and taking expectations at time t , we can write the following expression for the log cap rate:

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

It should be noted that this log linearization is valid only if expected returns and rent growth rates

¹Hotel properties represent another category of commercial real estate. Unfortunately, we do not have data on hotels and so they are excluded from our subsequent analysis. However, hotels represent less than four percent of the total value of U.S. commercial real estate. See Case (2000).

²Net rents require the tenant, as opposed to the landlord, to be responsible for operating expenses such as electricity, heat, water, maintenance, and security (see Geltner and Miller (2000)). When there is no possibility of confusion, we will refer to net rents simply as rents.

³In particular, $\rho \equiv 1/(1 + \exp(\bar{h} - \bar{p}))$ where $\bar{h} - \bar{p}$ denotes the average log rent - price ratio. Note that for the US commercial real estate market, the average rent - price ratio across property types and metropolitan areas for the 1994 - 2003 sample period is approximately 9% on an annual basis, implying an annualized value for ρ of 0.92. This is lower than the 0.98 annualized value of ρ for the aggregate stock market during the same period.

are both stationary. Whether or not this is the case in our commercial real estate data will be investigated later.

The preceding expression for the cap rate is best understood as a consistency relation. If a commercial property's cap rate is high, then either the property's expected return is high, or the growth of its rents is expected to be low, or both. This log-linearization framework was proposed by Campbell and Shiller as a generalization of Gordon's (1962) constant-growth model and explicitly allows both expected returns and dividend growth rates to be time-varying. Like other assets, there are good reasons to believe that expected returns to commercial real estate and rent growth rates are both time-varying. We use expression (2) as the starting point for our analysis of fluctuations in commercial real estate prices.⁴

For a particular property type in a specific area, expression (2) states that the cap rate forecasts either expected returns or expected growth in rents, or both. This is usually tested by estimating the following system:

$$r_{t+1} = \alpha + \beta(cap_t) + \varepsilon_{t+1}^r \quad (3)$$

$$\Delta h_{t+1} = \mu + \lambda(cap_t) + \varepsilon_{t+1}^h \quad (4)$$

$$cap_{t+1} - c = \phi(cap_t - c) + \varepsilon_{t+1}^c. \quad (5)$$

Expressions (3) and (4) are predictive regressions which relate future returns and rent growth, respectively, to today's cap rate while expression (5) describes the dynamics of the cap rate. We collect the residuals of these regressions in the vector $\varepsilon_{t+1} = [\varepsilon_{t+1}^r, \varepsilon_{t+1}^h, \varepsilon_{t+1}^c]$ and denote its variance-covariance matrix by Σ_ε . Predictive regressions have been extensively analyzed in the context of the stock market by, among others, Campbell and Shiller (1988b), Fama and French (1988), Cochrane (2008), and Lettau and Van Nieuwerburgh (2008). As emphasized by this literature, absent any further assumptions, the residuals ε_{t+1} have no clear economic interpretation and are simply forecasting or measurement errors. In the same spirit, expressions (3)-(5) are best interpreted as the reduced form of an underlying data generating process that is usually left unspecified.

Like much of the predictability literature, we estimate these regressions in-sample. That is, our estimates of the parameters of these predictive regressions are based on the entire sample and

⁴To the extent that this expression holds for any property type in any particular area, without loss of generality, we will simplify our subsequent notation by simply keeping track of the time subscript.

not just the data available at the time a particular cap rate observation is realized. Therefore, as emphasized by Goyal and Welch (2008), these results be taken as documenting ex-post variation in conditional means rather than an ex-ante forecasting relation. An important insight of the predictability literature is that the forecasting ability of a slowly moving predictor may be more easily discerned at long horizons as opposed to short horizons. That being the case, we will test whether cap rates forecast future returns and rent growth over a horizon of $k > 1$ periods:

$$r_{i,t+1 \rightarrow t+k} = \alpha_k + \beta_k (\text{cap}_t) + \varepsilon_{t+1 \rightarrow t+k}^r \quad (6)$$

$$\Delta h_{i,t+1 \rightarrow t+k} = \mu_k + \lambda_k (\text{cap}_t) + \varepsilon_{t+1 \rightarrow t+k}^h \quad (7)$$

where $r_{t+1 \rightarrow t+k} \equiv \sum_{i=0}^k r_{t+1+i}$ and $\Delta h_{t+1 \rightarrow t+k} \equiv \sum_{i=0}^k \Delta h_{t+1+i}$ proxy for expected returns and expected rent growth rates, respectively. Under the assumption that the cap rate follows an $AR(1)$ process with autoregressive coefficient ϕ , as described by expression (5), the short-horizon and corresponding long-horizon coefficients of the predictive regressions⁵ are related by:

$$\beta_k = \beta \left(\frac{1 - \phi^k}{1 - \phi} \right) \quad \text{and} \quad \lambda_k = \lambda \left(\frac{1 - \phi^k}{1 - \phi} \right). \quad (8)$$

We will be able to gain further economic insights into the results of these predictive regressions if additional structure is imposed on the dynamics of returns and rent growth rates. To do so requires that we first introduce our commercial real estate data and describe its time-series and cross-sectional properties.

2.2 Commercial Real Estate Data

Our commercial real estate data consists of prices, $P_{i,t}^m$, and cap rates, $CAP_{i,t}^m$, of class A offices, apartments, retail and industrial properties located in fifty-three U.S. metropolitan areas and are provided by Global Real Analytics (GRA). The prices and cap rates for each property type in a particular area are value-weighted averages of corresponding transactions data in a given quarter.⁶ Class A buildings are investment-grade properties that command the highest rents and sales prices

⁵In what follows, the coefficients β and λ always refer to the corresponding one-period regression coefficients, while the subscript k applies to long-horizon regression coefficients.

⁶GRA will not disclose details surrounding the construction of their data series apart from the fact that all averages for a particular property type are value-weighted and are based on at least twelve transactions within a metropolitan area in a given quarter. Cap rates are calculated based on net rents.

in a particular market.⁷ The fifty-three sampled areas encompass more than 60% of the U.S. population. A listing of these metropolitan areas is given in Appendix A. The data are available on a quarterly basis beginning in the second quarter of 1994 (1994:Q2) and ending in the first quarter of 2003 (2003:Q1). Taken together, we have panel data consisting of 1908 observations (36 quarters \times 53 metropolitan areas).⁸

We use the given $P_{i,t}^m$ and $CAP_{i,t}^m$ to construct quarter t 's net rents as $H_{i,t}^m = (CAP_{i,t}^m \times P_{i,t}^m)/4$.⁹ The gross returns $1 + R_{i,t}^m$ in quarter t are then obtained from expression (1) while $H_{i,t}^m/H_{i,t-1}^m$ gives one plus the growth in rents. For consistency, we work with log cap rates, $cap_{i,t}^m = \ln(CAP_{i,t}^m)$, and log rent growth rates, $\Delta h_{i,t}^m = \ln(H_{i,t}^m/H_{i,t-1}^m)$. We also rely on log excess returns, $r_{i,t}^m = \ln(1 + R_{i,t}^m) - \ln(1 + TBL_t)$, where TBL denotes the three month Treasury bill yield.¹⁰

Our returns and rent growth series are based exclusively on transactions data and are available across a cross-section of metropolitan areas. By concentrating only on class A buildings, GRA attempts to hold property quality constant both within a particular metropolitan area as well as across metropolitan areas.¹¹ While these particular indices are no longer publicly available, they serve as the basis of GRA's recent efforts in conjunction with Standard & Poor's to offer a series of commercial real estate indices for the trading of commercial real estate futures and options on futures on the Chicago Mercantile Exchange.

Table 1 presents summary statistics of the key variables in our analysis - excess returns, rent growth rates, and cap rates - during the 1994:Q2 to 2003:Q1 sample period. We report time-series averages, standard deviations, and serial correlations at both one-quarter and one-year lags. We also report t -statistics testing the null hypotheses of no serial correlation in the excess returns and rent growth series as well as the augmented Dickey-Fuller (ADF) statistic testing the null hypothesis of a unit root in the cap rate series. In the interest of brevity, we report only the averages of these statistics across the fifty-three sampled metropolitan areas for each of the four

⁷Class B buildings, by contrast, are less appealing and are generally deficient in floor plans, condition and facilities. Class C buildings are older buildings that offer basic services and rely on lower rents to attract tenants.

⁸A subset of these data are available for twenty-one of the metropolitan areas going back to 1985:Q4 and ending in 2002:Q4 but only at a bi-annual frequency.

⁹We obtain very similar results by modifying the timing convention and relying on the expression $H_{i,t}^m = (CAP_{i,t}^m \times P_{i,t-1}^m)/4$.

¹⁰We use excess returns throughout the paper, since our main interest is in variation in risk premia. When we use real rather than excess returns, the results are very similar (see also Cochrane (2008)). For the sake of brevity, excess returns will be referred to simply as returns.

¹¹Commercial real estate turns over far less frequently than residential real estate. This extremely low turnover rate, especially in certain metropolitan areas, makes it difficult to construct a repeat-sales index for commercial properties.

commercial property types.

From Table 1 we see that the average annualized excess returns of the commercial properties range from 7.3% (offices) to 9.5% (apartments) while the average annualized standard deviations lie between 3.7% (retail) and 6.1% (apartments). By comparison, the corresponding average annualized return of the CRSP-Ziman REIT value-weighted index is comparable at 8.8% but with a standard deviation of 12.4%. The higher volatility of the REIT index reflects the fact that REITs are leveraged investments that are traded much more frequently than commercial real estate properties.¹²

The commercial property excess return series have low serial correlations at a one-quarter lag and virtually none at a yearly lag. For each property type, the average serial correlation at a one-quarter lag is not statistically significantly different from zero. The number of significant one-quarter autocorrelations for any particular property type located in a given metropolitan area (not displayed) is small. Only for offices is the average serial correlation at a one-quarter lag relatively high but it remains statistically indistinguishable from zero. At an annual lag, the excess return series are, on average, close to uncorrelated for all property types. Similarly, very few one-year autocorrelations for a particular property type located in a given metropolitan area are statistically significant (not displayed). While serial correlation tests may have little power, the general message that emerges is that these excess returns do not appear to suffer from the high autocorrelations which plague appraisal-based series.¹³

The autocorrelation properties of the rent growth series are similar, exhibiting modest serial correlations at both one-quarter and one-year lags. The lack of persistence in the excess returns and rent growth series can also be seen in the respective values of the t -statistics given in the final column of Table 1 which indicate that we cannot reject the null hypothesis of zero first-order autocorrelations in either series.

Turning our attention to cap rates, the annualized average cap rates in Table 1 range from 8.9% (apartments) to 9.3% (retail) and lie between the estimates of Liu and Mei (1994), who report average cap rates for commercial real estate of approximately 10.4%, and Downing, Stanton, and

¹²During the same sample period, the annualized return of the CRSP value-weighted stock market index had a mean and standard deviation of 8.4% and 19.2%, respectively, while the annualized three-month Treasury bill rate had a mean and standard deviation of 4.5% and 0.7%, respectively.

¹³See Geltner (1991) for a detailed discussion of this issue.

Wallace (2008)'s range of 7.8% to 8.5%.¹⁴ In contrast to the excess return series, however, the cap rate series are extremely persistent. The average first-order serial correlation at a quarterly lag lies between 0.759 (industrial) and 0.846 (offices) and we obtain serial correlation estimates close to unity for commercial properties located in many metropolitan areas (not displayed). The final column of Table 1 reports the average *ADF* statistic under the null hypothesis of a unit root in the cap rate series. As can be seen, this null hypothesis cannot be rejected for any of the property types, though we also cannot reject local-to-unity alternatives such as $\phi = 0.99$.¹⁵

The time-series properties of the cap rates have important implications for our subsequent empirical analysis. In particular, it is well known that persistence in a forecasting variable complicates the estimation of a predictive regression. In addition, any non-zero correlation between shocks to the predictor variable and shocks to the dependent variable induces a bias in the slope estimate of a predictive regression. Several papers including, among others, Stambaugh (1999), Nelson and Kim (1993), Lewellen (2004), Torous, Valkanov, and Yan (2005), and Paye and Timmermann (2006), address these and other issues in the estimation of a predictive regression. This research demonstrates that first-order asymptotic normality results are not reliable when applied to predictive regressions in small samples. While several improvements in estimating predictive regressions have been suggested, these improvements are difficult to apply in our setting because of the panel nature of our data as well as our relatively short sample period. In addition, we do not have an *i.i.d.* cross-sectional sampling scheme as is usually assumed in panel data studies.

For these reasons, our estimation of predictive regressions will rely on a double resampling procedure which takes into account the bias inherent in the predictive regression's slope estimate, the overlapping nature of long horizon regressions, and the cross-sectional correlation in cap rates across metropolitan areas. This procedure, which extends Nelson and Kim (1993)'s approach to a panel data setting, allows us to address these various estimation issues while directly accounting for our small sample size by relying on a bootstrap methodology.

An alternative approach to deal with the persistence of a predictor variable in a predictive regression is to argue that this persistence reflects occasional structural breaks in the series (Paye and Timmermann (2006) and Lettau and Van Nieuwerburgh (2008)). For example, Lettau and

¹⁴The average dividend-price ratio for the CRSP-Ziman REIT Value-Weighted Index over this sample period is 6.8%.

¹⁵These ϕ estimates also suffer from a downward bias (Andrews (1993)) which our subsequent estimation procedure must address.

Van Nieuwerburgh (2008) identify breaks in the aggregate stock market's dividend yield series and demonstrate that accounting for these breaks has an important effect on the stochastic behavior of the series and, more importantly, on predictability tests.

We also test for structural breaks in our cap rate series by property type using Perron's (1989) sup- F test for breaks with unknown location. We consider both our main 1994:Q2 to 2003:Q1 sample period as well as the extended 1985:Q4 to 2002:Q4 sample period. Only in the case of office properties over the extended sample period do we find evidence of a statistically significant break in cap rates. This break, identified in 1992, corresponds to the well documented collapse in the U.S. office property market in the early 1990s.¹⁶

The top panel of Figure 1 compares cap rates of commercial real estate on a national basis (solid line) with the dividend-price ratio of the stock market (dashed line) over the 1994:Q2 to 2003:Q1 sample period. The national commercial real estate cap series is calculated as the simple average of each of the four property type's national cap rate defined as a population-weighted average of the corresponding cap rates in the various metropolitan area.¹⁷ The stock market's dividend-price ratio is measured by the dividend price ratio of the CRSP value-weighted index. The average national cap rate is 9.1% while the average dividend-price ratio of the stock market over the same period is 1.7%. The bottom panel shows the same series on a biannual basis for the 1985:Q4 to 2002:Q4 sample period, where the dividend-price ratio series is break-adjusted in 1992 following the approach of Lettau and Van Nieuwerburgh (2008).¹⁸ As can be seen, the stochastic properties of the two series are remarkably similar. In fact, the correlation between the stock market's dividend-price ratio and the national cap rate is 0.769 for the 1994:Q2 to 2003:Q1 period and 0.687 during the 1985:Q4 to 2002:Q4 period. This high correlation suggests that, at least at the aggregate level, the stock market and the commercial real estate market are influenced by common factors.

To investigate their cross-sectional properties, Figure 2 plots the cross-sectional distribution of cap rates for each of the four property types. The figure displays mean cap rates as well as their 5th and 95th percentiles across the fifty-three metropolitan areas. As can be seen, cap rates exhibit considerable cross-sectional variation. For example, the average cross-sectional standard deviation

¹⁶The difference in average office cap rates before versus after the estimated break is +0.78%. This result is consistent with, for example, the 24% drop in the level of the NCREIF office index between 1991 and 1992. No other NCREIF property index experienced a similar drop around this time period.

¹⁷Calculating the national cap rate as an average of equally weighted series gives a very similar picture.

¹⁸The national commercial real estate cap series does not exhibit any statistically significant breaks.

in cap rates for offices is 0.58%, which is more than one and a half times the corresponding average time-series standard deviation of 0.37%. The average difference between the 5th and 95th percentiles of these distributions provides another measure of the cross-sectional variation in cap rates. In the case of apartments, the average difference between the 5th and 95th percentiles is 1.8% which is large when we recall that the average cap rate for apartments across metropolitan areas is 8.9%. This average difference is the largest for offices at 2.1%.

Finally, we can also measure the cross-sectional dispersion in cap rates by looking at the average R^2 from regressing the individual cap rates on the national average for each corresponding property type. Consistent with the previous findings, the average R^2 is lowest for offices at 0.26 while increasing to 0.36 and 0.46 for industrial and retail properties, respectively. Even in the case of apartments, which display the highest degree of cross-sectional dispersion, the average R^2 is only 0.55. To the extent that this considerable dispersion in cap rates reflects differences in expectations about future returns or rent growth rates across metropolitan areas, it represents valuable cross-sectional information which we can exploit to improve the results of our predictability tests.

2.3 Expected Returns and Expected Growth in Rents

Guided by these empirical properties, we now impose additional structure on our specification of commercial property returns and rent growth processes. The resultant framework allows us to not only investigate in more detail the economic properties of our commercial real estate data but also to link the reduced-form predictive regressions to an underlying structural model. This approach is used by Lettau and Van Nieuwerburgh (2008) to model aggregate stock market returns.

In particular, we assume

$$r_{t+1} = r + x_t + \xi_{t+1}^r \tag{9}$$

$$\Delta h_{t+1} = g + \tau x_t + y_t + \xi_{t+1}^h \tag{10}$$

where ξ_{t+1}^r represents an unexpected shock to commercial real estate returns and ξ_{t+1}^h is an unexpected shock to rent growth with $E_t(\xi_{t+1}^r) = E_t(\xi_{t+1}^h) = 0$. Taking expectations, gives

$$\begin{aligned} E_t r_{t+1} &= r + x_t \\ E_t \Delta h_{t+1} &= g + \tau x_t + y_t \end{aligned}$$

where the variables x_t and y_t capture time variation in expected returns and expected rent growth, respectively. Notice that x_t also enters into the equation describing expected rent growth. This will allow us to investigate whether expected returns and expected rent growth are correlated in the commercial real estate market. We model the variations x_t and y_t as mean-zero first order autoregressive processes:

$$x_{t+1} = \phi x_t + \xi_{t+1}^x \quad (11)$$

$$y_{t+1} = \phi y_t + \xi_{t+1}^y \quad (12)$$

where ξ_{t+1}^x and ξ_{t+1}^y are mean zero innovations in expected returns and expected rent growth, respectively.¹⁹ The system of equations (9)-(12) represents the structural model underlying the reduced-form predictive regressions. The four structural shocks of the system will be collected in the vector $\xi_{t+1} = [\xi_{t+1}^r, \xi_{t+1}^h, \xi_{t+1}^x, \xi_{t+1}^y]$ and the variances of these shocks are denoted by $\sigma_{\xi^r}^2, \sigma_{\xi^h}^2, \sigma_{\xi^x}^2$, and $\sigma_{\xi^y}^2$, respectively.

The covariance structure of the structural model's shocks must be consistent with the log-linearized cap rate formula given by expression (2). In particular, Campbell's (1991) variance decomposition implies that the structural shocks must satisfy:

$$\xi_{t+1}^r = \frac{\rho}{1 - \rho\phi} [(\tau - 1)\xi_{t+1}^x + \xi_{t+1}^y] + \xi_{t+1}^h \quad (13)$$

which guarantees identification of the structural model under the assumptions used to derive expression (2).

Since expression (13) imposes one restriction among the four structural shocks, we must characterize the covariance structure of three of these shocks. To identify x_{t+1} and y_{t+1} , we assume that their respective shocks are uncorrelated at all leads and lags, $Cov(\xi_{t+1}^y, \xi_{t+j}^x) = 0, \forall j$. In addition, we assume that $Cov(\xi_{t+1}^h, \xi_{t+j}^x) = 0 \forall j, Cov(\xi_{t+1}^h, \xi_{t+j}^y) = 0 \forall j \neq 1$, and $Cov(\xi_{t+1}^h, \xi_{t+1}^y) = \vartheta$. Imposing these assumptions on the covariance structure of the three unique shocks in ξ_{t+1} allow us to identify τ as the impact of the expected return component x_{t+1} on rent growth conditional on y_{t+1} . That is, τ captures any co-movement between expected returns and

¹⁹For simplicity, we assume that the autoregressive coefficients of the x and y processes are the same and are constant across the different metropolitan areas. While introducing area-specific ϕ values is an appealing extension, it would require the estimation of a much larger number of parameters which is not possible given our limited data. The modest cross-sectional variation in the cap rate's AR(1) coefficient across areas (not reported) suggests that such heterogeneity is not likely to be a first-order effect.

rent growth. For $\tau = 0$, the time variation in expected returns does not influence rent growth, while for $\tau = 1$, they move one for one. From these identifying assumptions, we can see that the variable y_t represents fluctuations in expected rent growth that are orthogonal to expected returns.

Using expressions (11) and (12), the cap rate can now be written as:

$$cap_t = \frac{r - g}{1 - \rho} + \frac{1}{1 - \rho\phi} [x_t(1 - \tau) - y_t]. \quad (14)$$

The first term in expression (14) reflects the difference between the unconditional expected return and the unconditional rent growth rate. The second term captures the influence of time-varying fluctuations in expected returns and rent growth rates on the cap rate. In particular, large deviations from the unconditional expected return (large x_t) or more persistent deviations (large ϕ) imply higher cap rates. Also, fluctuations in expected rent growth that are orthogonal to expected returns (y_t) are negatively correlated with cap rates. Finally, the autoregressive structure imposed on expected returns and expected rent growth implies that the cap rate itself follows an $AR(1)$ process with autoregressive coefficient ϕ (see the proof in Appendix B).

We can now explicitly relate the parameters of the reduced-form predictive regressions in expressions (3)-(4) to the structural parameters of the data generating system, expressions (9)-(12).²⁰ In particular, we can express the one-period predictive regression slope coefficients as follows:

$$\beta = \frac{(1 - \rho\phi)}{(1 - \tau) + v \frac{1}{1 - \tau}} \quad (15)$$

$$\lambda = \frac{-(1 - \rho\phi) [\tau(\tau - 1) + v]}{(1 - \tau)^2 + v} \quad (16)$$

where $v = \sigma_{\xi^y}^2 / \sigma_{\xi^x}^2$ captures the strength of the orthogonal shocks ξ^y in expected rent growth relative to the expected return shocks ξ^x .

This result makes it clear that it is the combined effect of the structural parameters τ and v which determines the sign and magnitude of the one-period predictive regression slope coefficients.²¹

²⁰All proofs are provided in Appendix B.

²¹We do not discuss the roles of the parameters ϕ and ρ because the former specifies the dynamics of an exogenous variable while the latter is a log-linearization constant which depends on the average cap rate and is seen to display little variation across property types (Table 1). In addition, notice from expressions (15) and (16) that as long as expected returns are stationary ($|\phi| < 1$), the quantity $(1 - \rho\phi)$ simply acts as a positive scaling quantity. This implies that ϕ and ρ do not affect the signs of the slope coefficients.

To better see this, the top two panels of Figure 3 plot the predictive coefficients β and λ for values of τ ranging between -1 and 1 given three empirically relevant v values. The case $\tau = 0$ corresponds to the common assumption made in the asset pricing literature (e.g., Campbell and Shiller (1988a), Cochrane (2008)) that expected returns do not affect cash flow growth rates. In this case, we see from expression (14) that the cap rate will be correlated with expected returns and expected rent growth rates. The one-period predictive slope coefficient from the return forecasting regression, expression (15), will be positive for $\tau = 0$ while the corresponding coefficient from the rent growth forecasting equation, expression (16), will be negative. By contrast, for $\tau = 1$, expected rental growth rates move one for one with expected returns and the cap rate in expression (14) will be unable to detect fluctuations in expected returns, $\beta = 0$, because the variation in expected returns will be exactly offset by corresponding fluctuations in expected rent growth rates. This can also be seen from expression (15) where $\beta = 0$ for $\tau = 1$. In this case, however, λ remains negative because the cap rate is still negatively related to the future growth in rents, expression (14).²²

The link between return predictability and cash flow predictability, discussed recently by, among others, Cochrane (2008) and Lettau and Van Nieuwerburgh (2008), is also evident in the top two panels of Figure 3. For each value of v , we see that as return predictability increases from $\tau = 0$ through approximately $\tau = 0.5$, the rent growth rate predictability coefficient λ decreases in absolute value. The opposite holds for subsequent τ values. In other words, for given values of the structural parameters, we must either observe return predictability, or rent growth predictability, or both. This result is a restatement of the present value relation (13) which, as pointed out in the context of the aggregate stock market by Lettau and Van Nieuwerburgh (2008), can also be expressed as a restriction between the predictive regression coefficients β and λ :

$$\beta - \lambda = 1 - \rho\phi. \tag{17}$$

This economic restriction also accounts for the similarity of the plots in the top two panels of Figure 3 as the difference between β and λ must equal a constant for all values of the underlying structural parameters τ and v .

The effects of the structural parameter v on the reduced-form parameters are explored in the bottom two panels of Figure 3 for three empirically relevant τ values. Since v is defined as

²²While negative values of τ are theoretically possible and are displayed in Figure 3, we will see that the τ estimates for our commercial real estate data suggest that expected returns and expected rental growth rates are positively correlated.

the strength of the orthogonal shocks in expected rent growth relative to expected return shocks, it plays an important role in determining the magnitude of β as well as the magnitude and sign of λ .²³ In the return predictability regression, v can be interpreted as a noise-to-signal ratio as its numerator $\sigma_{\xi^y}^2$ captures the variation in ξ^y orthogonal to expected return fluctuations. As v increases, the signal from time-varying expected returns is dominated by orthogonal fluctuations in expected rent growth and return predictability becomes difficult to detect. Consequently, β decreases towards zero. By contrast, in the rent growth predictability regression, v plays exactly the opposite role. It can now be interpreted as a signal-to-noise ratio because $\sigma_{\xi^y}^2$ captures the signal in the regression predicting rent growth rates. Therefore, as v increases, predictions in the rent growth regressions become sharper.

Explicitly linking the underlying structural parameters to the predictive regression's reduced-form coefficients has economic as well as econometric advantages. In particular, the constraint given by expression (17) provides a link between the reduced-form estimates and the underlying structural model, thus allowing us to identify the sources of predictability.²⁴ We can also exploit two important restrictions which follow from this analysis in our empirical work. First, imposing this constraint allows us to jointly estimate the one-period predictive regression coefficients β and λ . Second, since the one-period predictive regression coefficients β and λ are related to the corresponding long-horizon predictive regression coefficients β_k and λ_k by expression (8), we will impose these cross-equation restrictions at a given horizon as well as across horizons in estimating β and λ . Both of these restrictions will lead to efficiency gains which takes on additional importance given our limited sample period.

From the system of expressions (9)-(13), we can also derive the proportion of the variance of returns and rent growth due to time-variation in their unobservable expectations. These statistics correspond, respectively, to the R^2 s obtained when regressing realized returns on $E_t r_{t+1}$ (denoted by R_{Er}^2), and realized rent growth rates on $E_t \Delta h$ (denoted by $R_{E\Delta h}^2$). Kojien and Van Binsbergen (2009) propose these measures in their investigation of stock market predictability. While the

²³We restrict our attention to the economically relevant case of $v > 0$. In the degenerate case $v = 0$, the expected growth in rents is entirely driven by shocks to expected returns when there are no orthogonal shocks to expected rent growth.

²⁴It should be noted that the identification of the structural parameters relies on the assumption that agents are forming their expectations rationally. If this were not the case, the Campbell and Shiller (1988b) decomposition ceases to be a valid description of the underlying data generating process as it would suffer from an omitted variable bias. This, in turn, would bias the interpretation of the structural parameters, but not the results from estimating the predictive VAR, equations (3-5).

identification and estimation of their underlying structural model differs from ours, using similar R^2 -based statistics will allow us to compare the observed time variation in commercial real estate to that of common stock.

It is important to realize that the statistics R_{Er}^2 and $R_{E\Delta h}^2$ are based on the structural relations posited to prevail in the commercial real estate market. Therefore, they may differ substantially from those calculated in simple predictive regressions, such as expressions (3) and (4). To see the difference, consider the extreme case where expected returns and expected rent growth rates are time-varying and highly correlated so that $\tau = 1$. Under this assumption, the cap rate will be unable to forecast future returns despite the fact that expected returns are time-varying and the R^2 of the predictive regression (3) will be zero. However, R_{Er}^2 will be non-zero in this case and will be able to properly measure the magnitude of time-variation in expected returns.

3 Empirical Results

3.1 Estimation Method

We use a Generalized Method of Moments (GMM) procedure to estimate the long-horizon predictive regressions, expressions (6) and (7), by imposing both the present value restriction, expression (17), as well as the restriction between short-horizon and long-horizon coefficients given in expression (8). We estimate these regressions in-sample at forecast horizons of $k = 1, 4, 8$ and 12 quarters and the moments we use are the standard OLS orthogonality conditions. Taken together, we have a total of eight equations (four horizons for each of the two regressions) and two unknowns (β and λ). We rely on the pooled sample of fifty-three metropolitan areas over the 1994:Q2 to 2003:Q1 sample period for each of the four commercial property types.

It is important to emphasize that our pooled regressions differ from the time-series regressions used in the stock return predictability literature. Given the limited time period spanned by our data, this pooled approach has a number of advantages. Because we are primarily interested in long-horizon relations but, unfortunately, do not have a sufficiently long time series, the only statistically reliable means of exploring these relations is to rely on pooled data. Also, as previously demonstrated, there is considerable heterogeneity in returns, rent growth rates, and cap rates across metropolitan areas at any particular point in time. Therefore, tests based on the pooled regressions

are likely to have higher power than tests based on time-series regressions in which the predictive variable has only a modest variance (Torous and Valkanov (2001)).

Before presenting our results, we address a number of statistical issues concerning our pooled predictive regression framework. First, the overlap in long-horizon returns and rent growth rates must be explicitly taken into account. In our case, this overlap is particularly large relative to the sample size. In addition to inducing serial correlation in the residuals, this overlap induces persistence in the regressors and, as a result, alters their stochastic properties. While this problem has been investigated in the context of time-series regressions, it is also likely to affect the small-sample properties of the estimators in our pooled regressions. Second, the predictors themselves are cross-sectionally correlated. By way of example, the median cross-sectional correlation of apartment cap rates in our sample is 0.522 and is as high as 0.938 (between Washington, DC and Philadelphia). Because we effectively have fewer than fifty-three independent cap rate observations at any particular point in time, a failure to account for this cross-sectional dependence will lead to inflated t -statistics. Finally, the cap rates are themselves persistent and their innovations are correlated with the return innovations. Under these circumstances, it is well known that, at least in small-samples, least squares estimators of a slope coefficient will be biased in time-series predictive regressions (Stambaugh (1999)). In pooled predictive regressions, the slope estimates will also exhibit this bias because they are effectively weighted averages of the biased slope estimates of the time-series predictive regressions for each metropolitan area.

As a result of these statistical issues, traditional asymptotic methods are unlikely to provide reliable inference in our pooled predictive regression framework. As an alternative, we rely on a two-step resampling approach. In the first step, as is customary when estimating any predictive regression, we run time-series regressions for each of the fifty-three metropolitan areas in which one-period returns and rent growth rates are individually regressed on lagged cap rates while the cap rates themselves are regressed on lagged cap rates. The coefficients and residuals from these regressions are subsequently stored. For each area we then resample the return residuals, rent growth residuals and cap rate residuals jointly across time (without replacement, as in Nelson and Kim (1993)). The randomized return and rent growth residuals are used to create one-period returns and rent growth rates, respectively, under the null of no predictability. To generate cap rates, we use the corresponding coefficient estimates together with the resampled residuals from the cap rate autoregression. For each resampling i , we then form overlapping multi-period returns

and rent growth rates from the resampled single-period series and obtain GMM estimates $(\hat{\beta}^i, \hat{\lambda}^i)$.

This first step is used to obtain estimates of the small sample bias of the slope coefficients as the contemporaneous correlations between the return or rent growth residuals and cap rate residuals in a given metropolitan area as well as across areas are preserved. Because these data are generated under the null, the average $\hat{\beta}$ across resamplings, denoted by $\bar{\beta} = \frac{1}{I} \sum_{i=1}^I \hat{\beta}^i$, estimates the bias in the pooled predictive regression. The bias-adjusted estimate of β is obtained as $\hat{\beta}^{adj} = \hat{\beta} - \bar{\beta}$, where $\hat{\beta}$ is the biased estimate of β obtained from the pooled GMM estimation. The bias-adjusted estimate for the rent growth predictive regression, $\hat{\lambda}^{adj}$, is similarly constructed. This procedure is in essence that suggested by Nelson and Kim (1993) but applied to a pooled regression. However, while this procedure captures the overlap in the multi-period returns, it does not address the cross-sectional dependence in cap rates.

This then necessitates our second step. To account for the possibility that our predictability results are driven by cross-sectional correlation in cap rates, we resample the cap rates across metropolitan areas at each point in time for each forecast horizon.²⁵ Then, for a given cross-section, we estimate the predictive regression using the two-stage GMM procedure thus obtaining T estimates $(\hat{\beta}^s, \hat{\lambda}^s)$, where T is the sample size for which we can construct GMM estimates using all horizons and the superscript s denotes cross-sectional estimates from the resampled data. We repeat the entire resampling procedure 1,000 times which gives $1,000 \times T$ estimates $(\hat{\beta}^s, \hat{\lambda}^s)$. We use these $1,000 \times T$ estimates to compute standard errors, denoted by $se(\beta)$ and $se(\lambda)$, respectively. This second step is very similar to a standard Fama and MacBeth (1973) regression with the exception that we are running the regressions with 1,000 replications of bootstrapped data rather than the original data.

The standard errors from the double resampling procedure account for both time-series and cross-sectional dependence in the data. In the first resampling step, the overlapping nature of the regressors is explicitly taken into account, while in the subsequent resampling step, at each point in time the cap rates are drawn from their empirical distribution. The bias-adjusted double resampling t statistic, denoted by t_{DR} , is computed as $t_{DR} = \hat{\beta}^{adj}/se(\beta) = (\hat{\beta} - \bar{\beta})/se(\beta)$, and analogously for λ . The 95th and 99th percentiles of the bootstrapped distributions of the t_{DR} statistic are used to assess the statistical significance in our empirical analyses. For the sake of clarity, we report

²⁵The bootstrap is carried out with replacement. We also attempted resampling without replacement and obtained very similar results.

levels of significance next to the estimates (5% and 1%) rather than small-sample critical values because the latter are a function of the overlap as well as the cross-sectional cap rate correlations of a particular property type.²⁶

3.2 Predictive Regression Results

Table 2 presents the bias-adjusted GMM estimates, $\hat{\beta}_k^{adj}$ and $\hat{\lambda}_k^{adj}$, as well as their corresponding t_{DR} statistics for each of the four property types based on the 1994:Q2 to 2003:Q1 sample period. The slope coefficients at the $k = 1$ quarter horizon and their t_{DR} statistics are obtained directly from the GMM procedure. The long-horizon coefficients for $k \geq 4$ quarters are then calculated using expression (8) where the required ϕ value is estimated by substituting the GMM estimates in the present value constraint expression (17). For these long-horizon slope coefficient estimates, the t_{DR} statistics are then calculated using the delta method. Statistical significance at the 5% and 1% levels are denoted by superscripts “a” and “b”, respectively. For comparison with previous results, we also provide the R^2 statistics for OLS regressions of future returns on log cap rates (R_r^2) and future rent growth on log cap rates ($R_{\Delta h}^2$), estimated separately.

For all property types, we see that at the short horizon of $k = 1$ quarter, cap rates are positively correlated with future returns. Retail properties have the largest bias-adjusted slope coefficient, $\hat{\beta}^{adj} = 0.111$, and office properties have the smallest, $\hat{\beta}^{adj} = 0.027$. For all property types except offices, the corresponding bias-corrected slope coefficients are statistically significant. Regardless of the property type, however, cap rates explain very little of return variability at the $k = 1$ quarter horizon as evidenced by the low R_r^2 statistics reflecting the large variability in quarterly commercial property returns.

As the return horizon lengthens, $k \geq 4$ quarters, the bias-corrected slope coefficients $\hat{\beta}_k^{adj}$ increase in magnitude and provide reliable evidence of return predictability in the case of apartments, industrial and retail properties. The predictive regressions also explain an increasingly

²⁶A few additional points are worth mentioning about the our resampling procedure. First, the second bootstrap is necessary in order to take into account the cross-sectional correlation in cap rates. Without it, the standard errors would not be corrected for the cross-sectional dependence in cap rates. We verified that if we use only the Nelson and Kim (1993) randomization, we obtain t statistics very similar to the Newey and West (1987) results. Second, it is interesting to note that the pooled regression does not produce unbiased estimates. The reason is that given the cross-sectional correlation in cap rates and the fact that cap rate fluctuations and return shocks are correlated, the pooled regression effectively yields a weighted average of the biased estimates that would have been obtained in time series regressions for each metropolitan area. Third, the bias-adjusted GMM estimates will take into account the fact that the bias tends to be larger at longer horizons, where the sample size is smaller and the overlap is larger.

larger proportion of the variability of these property returns at longer horizons. In the case of retail properties, the bias-corrected slope estimate increases to $\hat{\beta}^{adj} = 0.966$ at $k = 12$ quarters where the predictive regression can explain approximately 27% of the variability in returns. The explanatory power of the predictive regressions are somewhat smaller for apartments and industrial properties, explaining 15% of industrial property returns and 17% of apartment returns at the $k = 12$ quarter horizon.

In contrast to the other property types, there does not appear to be reliable evidence of return predictability at any horizon for offices. The bias-corrected slope estimates $\hat{\beta}_k^{adj}$ for offices are much smaller in magnitude and are never statistically significant. For example, at $k = 12$ quarters, the slope coefficient is $\hat{\beta}^{adj} = 0.247$, which is approximately half of the slope coefficient for apartments (0.468) and approximately one-quarter of that for retail properties (0.966). The corresponding R_r^2 statistics are also small for offices across all horizons, achieving a maximum of only 3.9% at a horizon of $k = 8$ quarters.

Turning our attention to the rent growth results presented in Table 2, it can immediately be seen that there is no reliable evidence that cap rates can forecast the future growth in rents of apartments, industrial and retail properties. Across all horizons, the bias-corrected slope coefficients $\hat{\lambda}_{adj}$ are not significantly different from zero and the corresponding $R_{\Delta h}^2$ statistics are small, between 0% and 3.1 %. By contrast, in the case of offices, the bias-corrected slope coefficients are negative and statistically significant. For example, the slope coefficient is $\hat{\lambda}_{adj} = -0.174$ with $t_{DR} = -2.261$ at a horizon of $k = 4$ quarters, increasing to $\hat{\lambda}_{adj} = -0.424$ with $t_{DR} = -2.238$ at a horizon of $k = 12$ quarters. However, the explanatory power of these regressions is small, the $R_{\Delta h}^2$ statistics never exceeding 2.3% ($k = 12$ quarters). The fact that the coefficients of the rent growth predictive regressions for offices are significant and large in absolute value is not surprising given that offices show the least return predictability and that the return and rent growth predictive regressions are related by the present value constraint, expression (17).

It is easier to interpret the implications of these regression results for the response of future commercial real estate returns to changes in cap rates as opposed to log cap rates. To do so, we divide the estimated slope coefficients by the average cap rate where the cap rate is expressed in the same units as returns (see, for example, Cochrane (2007)). For illustrative purposes, we compute these transformed coefficients for apartments, industrial properties, retail properties, and offices at the $k = 4$ quarter horizon using the corresponding $\hat{\beta}^{adj}$ estimates from Table 2 and their average

cap rates of 8.7%, 9.1%, 9.2%, and 8.7%, respectively. Based on these inputs, a one percent increase in cap rates implies that expected returns will increase at a horizon of $k = 4$ quarters by 2.1% for apartments, 3.0% for industrial properties, 4.6% for retail properties, and only 1.2% for offices. The same one percent increase in cap rates has a much smaller effect on expected rent growth rates, with the exception of offices where a decrease of approximately 2% at the $k = 4$ quarter horizon is implied.

3.2.1 Comparison with Common Stock

To better appreciate the effects of time-varying expected returns on commercial real estate, it is useful to compare our results to those obtained in the aggregate stock market. Lettau and Van Nieuwerburgh (2008) regress excess stock returns on the log dividend-price ratio over the 1992-2004 sample period and report a slope coefficient of 0.241 at a one-year horizon. Given an average dividend-price ratio of approximately 2% over their sample period, this implies that a one percent increase in the dividend-price ratio corresponds to approximately a 12% increase in expected stock returns. This rather strong response reflects the stock market's relatively low dividend-price ratio during the 1992-2004 period. Alternatively, using the stock market's 4% average dividend-price ratio over the 1927-2004 period, a one percent increase in the dividend-price ratio results in an increase in expected stock returns of approximately 6%, similar in magnitude to what we calculate in the case of commercial real estate. Lettau and Van Nieuwerburgh (2008) also report an R^2 statistic of 19.8% for their return predictive regression which is larger than what we find in the case of commercial real estate. However, for the longer 1927-2004 sample period, their R^2 statistic of 13.2% is comparable in magnitude to the explanatory power of our return predictive regressions when applied to commercial real estate.

3.2.2 Comparison with Other Real Estate Investments

It is also interesting to compare our results to the return predictability of residential real estate and real estate investment trusts (REITs). These assets have received more attention in the literature, primarily because of better data availability. Such a comparison will allow us to assess the extent to which our results are specific to commercial real estate as opposed to real estate investments in general. Anticipating our results, we note that, as documented by Wheaton (1999), different

types of real estate exhibit different cyclical patterns over time and their cycles also have differing correlations with the underlying business cycle. As a result, there is no *a priori* reason why return predictability patterns in residential real estate and REITs should coincide with those that we have documented in commercial real estate.

Residential Real Estate

Residential real estate is an important investment for U.S. households. Standard and Poor's estimates its value in 2007 at approximately \$22 trillion. Campbell, Davis, Gallin, and Martin (2009) rely on the dynamic Gordon model to investigate the economic determinants of the observed movements in the U.S. residential real estate market. Their conclusions as to what moves housing markets depends critically on whether their data is drawn from the post-1997 housing boom or not.

For the 1975-1996 sample period, the variability in housing's rent-price ratio at the national level is due to movements in risk premia while for the median of the sampled metropolitan areas Campbell, Davis, Gallin, and Martin (2009) conclude that movements in risk premia and movements in rent growth contribute equally to the variability in housing's rent-price ratio. These results are similar to the conclusions reached by Campbell (1991) as well as Campbell and Ammer (1993) for the aggregate stock market in which return variability is driven primarily by news about future returns as opposed to future dividends.

However, for the 1997-2007 sample period, which is closer to our sample period, movements in rent growth play the dominant role in explaining the variability in housing's rent-price ratio both at the national level as well as for the median of the sampled metropolitan areas. Therefore, Campbell, Davis, Gallin, and Martin's (2009) conclusion as to what moved housing markets during the housing boom period is the opposite of what they conclude for their earlier sample period. They are also contrary to our results, at least for apartments, retail and industrial properties, in which for a similar sample period we find that movements in future expected returns not future rental growth drive the variability of commercial real estate returns.

REITs

Institutions and individuals can participate in the commercial real estate market by investing in REITs. REITs are traded equity claims on commercial real estate but, unlike other common stock, they are subject to a strict payout policy because of their preferred tax status.²⁷

²⁷In particular, at least 90% of a REIT's net income must be paid out to shareholders in the form of dividends.

Using REIT data from CRSP, Liu and Mei (1994) explore time-variation in expected returns and dividend growth of REITs using a standard predictive regression approach. They find that cash flow news play a significant role in explaining the predictability of REIT returns. This result is attributed to the fact that dividends are a significant component of REIT returns owing to their strict payout policy. Moreover, they find that discount rate news is also an important component of return fluctuations.

Unfortunately, these findings are not directly comparable to ours for a number of reasons. First, Liu and Mei’s (1994) results are not disaggregated by property type but refer to the entire universe of REITs. Second, the REIT market is small and not representative of the U.S. commercial real estate market as a whole. For example, in 2007 there were 152 publicly traded REITs in the U.S. with a total market cap of only \$312 billion as compared to the approximately \$5.3 trillion of commercial real estate then outstanding. In addition, several studies document that REITs behave like small value stocks. For example, Liang and McIntosh (1998) conclude that REITs behave similarly to a highly leveraged portfolio of small cap stocks.²⁸ Chiang, Lee, and Wisen (2005) provide further evidence that REITs behave much like small value stocks. However, most asset pricing models have difficulty in explaining the returns of small value stocks (see, for example, Fama and French (1996) and Lewellen, Nagel, and Shanken (2009)). The fact that REIT returns are difficult to explain economically prevents a meaningful comparison with our results.

3.3 Structural Parameters

Given the vector of estimated reduced form parameters $\Theta = [\phi, \beta, \lambda, \Sigma_\varepsilon]$, we can imply the corresponding structural parameter vector $\Psi = [\phi, \tau, \sigma_{\xi^x}, \sigma_{\xi^y}, \sigma_{\xi^h}, \vartheta]$. To do so, we modify Lettau and Van Nieuwerburgh (2008)’s identification scheme to our setting. Details are provided in Appendix C. Panel A of Table 3 presents the underlying structural parameter estimates by property type based on quarterly observations over the 1994:Q2 to 2003:Q1 sample period. Estimates of other quantities derived from the implied structural parameter values are presented in Panel B of Table 3.

From Panel A we can clearly see that offices are distinguished by having the highest estimated

²⁸In fact, a more accurate characterization of REIT size would be of a few large REITs coupled with many much smaller REITs. This description is consistent with the fact that in 2009 the average market cap of REITs was \$1.37 billion while the median market cap was only \$.618 billion.

co-movement between their expected returns and expected rent growth, $\tau = 0.932$. By comparison, this co-movement is lower and roughly equivalent for retail properties ($\tau = 0.694$) and apartments ($\tau = 0.648$) and is lowest for industrial properties ($\tau = 0.275$). The volatilities of unexpected shocks to rent growth as well as to innovations in expected returns and expected rent growth are also largest for offices. Finally, the expected returns and expected rent growth of all commercial property types are found to be highly persistent with the implied autoregressive parameters ranging from $\phi = 0.972$ in the case of apartments to $\phi = 0.939$ for retail properties. In each case, however, we can reject the null hypothesis of a unit root.²⁹

While the largest noise-to-signal ratio v reported in Panel B is for apartments ($v = 0.254$), the other property types, including offices, are also characterized by a sizeable volatility of the orthogonal component of their rent growth processes. These v estimates taken together with the corresponding τ estimates explain our previously documented predictability patterns. In particular, the very high co-movement between expected returns and rent growth for offices together with their sizable noise-to-signal ratio makes it difficult for office cap rates to forecast returns to offices. For example, offices and industrial properties are characterized by similar noise-to-signal ratios but τ is much higher for offices. With reference to Figure 3, this implies that the return predictability slope coefficient β is much lower for offices than industrial properties. Equivalently, the rent growth predictability coefficient λ will be larger (in absolute value) for offices than industrial properties.

Panel B of Table 3 also displays the implied annualized volatilities of commercial real estate returns and the volatilities of their conditional expectations. Looking across property types, apartment returns are the most volatile at 7.3%, followed by industrial properties (6.2%) and offices (6.1%). Returns to retail properties are the least volatile at only 4.4%. Expected returns to all commercial property types including offices can be seen to be time-varying. In fact, the volatility of expected returns to offices is highest among all property types at 2.5%. The volatilities of expected returns to apartments and retail properties follow in magnitude, at 2.1% and 1.9%, respectively. Expected returns to industrial properties are least volatile at 1.3%.

Rent growth is seen in Panel B to be most volatile for offices, 5.7%, and least volatile for retail properties at 3.9%. Industrial properties and apartments exhibit similar rent growth volatility, 4.6% and 4.5%, respectively. Expected rent growth is also highest for offices at 2.5%, while industrial properties exhibit the lowest time variation in expected rent growth, approximately 0.7%. Retail

²⁹Relying on the delta method applied to the present value constraint.

properties and apartments lie in between, at 1.5% and 1.7%, respectively.

To measure the relative importance of fluctuations in market expectations on movements in commercial real estate returns and rent growth, Panel C of Table 3 reports the implied R_{Er}^2 statistic from regressing returns on expected returns as well as the implied $R_{E\Delta h}^2$ statistic from regressing rent growth on expected rent growth. The R_{Er}^2 statistics range from 19.7% for retail properties to 4.4% for industrial properties. Notice that offices have the second highest R_{Er}^2 statistic at 16.3%. This result is in contrast to the lack of office return predictability observed in Table 2. The difference reflects the large co-movement between office expected returns and growth in office rents captured by the corresponding $\tau = 0.932$ estimate in Panel A of the Table. Offices exhibit the highest rent growth predictability with an $R_{E\Delta h}^2$ statistic of 19.7%. Industrial properties again exhibit the least time-variation in their rent growth, about 2%. Time-varying expected rent growth explains approximately 15% of the variance of the rent growth of apartments and retail properties. By comparison, Kojien and Van Binsbergen (2009) document that time-variation in expected returns explain about 8.5% of the variance of aggregate stock market returns while time-variation in expected dividend growth rate explains between 15% to 40% of the variance of the aggregate stock market's dividend growth rate. Thus, all commercial property types except industrial properties exhibit comparable or even greater time-variation in their expected returns and expected cash flow growth rates.

The picture that emerges from Table 3 differs from that in Table 2. The R_{Er}^2 and $R_{E\Delta h}^2$ statistics reveal substantial time variation in both expected returns and expected rent growth rates in the commercial real estate market. The positive co-movement of expected returns and expected rent growth rates renders the cap rate an unreliable forecaster in reduced form regressions, especially for offices. It is natural then to ask whether variables other than the cap rate are able to capture the fluctuations in expected returns and expected rent growth. We explore this issue further in Section 4.

3.4 Robustness Checks

We next investigate the robustness of our results to a variety of statistical and empirical issues. This will ensure that our conclusions are not a consequence of relying on a misspecified model which ignores heterogeneity across metropolitan areas or, alternatively, are specific to the 1994:Q2 to 2003:Q1 sample period. The impact of the overlapping nature of the long-horizon returns and

rent growth rates that we rely on is also investigated.

3.4.1 Longer Sample Period with Fewer Metropolitan Areas

An important question to ask is whether our results hold over a longer sample period or are they specific to the 1994:Q2 to 2003:Q1 sample period? For example, this time period contains only one full business cycle and coincides with a general upward trend in commercial real estate prices. The precipitous drop in commercial real estate prices, especially office buildings, during the early 1990s is avoided.

To answer this question, we extend the sample back to 1985 by augmenting our data with bi-annual observations available from GRA for a subset of twenty-one of the fifty-three metropolitan areas. These data begin with the second half of 1985 and extend until the first half of 1994, to which we then add the post-1994 observations for the twenty-one areas but sampled at a bi-annual frequency. This results in a sample from 1985 to 2002 containing thirty-five semi-annual observations for each of the twenty-one metropolitan areas, giving a total of 735 observations per property type. We rely on these data to investigate the stability of our predictability findings but at a cost of fewer cross-sectional observations.³⁰

Using data from the 1985 to 2002 sample period, we re-estimate the predictive regressions, expressions (3) and (4). The results are presented in Table 4. Cap rates can still be seen to forecast returns for apartments as well as retail and industrial properties, especially at longer horizons, $k \geq 8$ quarters. The bias-adjusted slope coefficients are now slightly larger than previously reported for apartments and industrial properties, but are similar in magnitude to those previously reported in the case of retail properties. Their significance, however, as measured by the corresponding t_{DR} statistics, is slightly lower in the extended sample period. For these property types, we see that cap rates still cannot forecast rent growth. As before, we also see that cap rates cannot forecast returns to offices at any horizon. However, while the estimated coefficients are still negative, cap rates no longer forecast office rent growth over the extended sample period.

The structural parameter estimates corresponding to the underlying commercial real estate data generating process over the 1985 to 2002 sample period are presented in Table 5. The estimated co-movement between expected returns and expected rent growth, τ , is still the highest for office

³⁰As noted earlier, the office cap rate series is break-adjusted in 1992 following the approach of Lettau and Van Nieuwerburgh (2008).

buildings as compared to the other commercial property types. Distinct from our previous results, however, the noisiness of the cap rate’s informativeness regarding future returns, as measured by the noise-to-signal ratio v , is now smallest for office properties. Notwithstanding this lack of noise, the high co-movement between expected returns and expected rent growth for offices means that office cap rates are unable to reliably forecast returns. Conversely, the fact the v is the smallest for offices implies that the rent growth predictive regression for offices is characterized by the lowest signal-to-noise ratio. As a result, office cap rates over the extended sample period no longer forecast rent growth.

Given these structural parameter estimates, we next investigate the time variation in commercial real estate expected returns and rent growth rates. Panel C of Table 4 displays the implied R_{Er}^2 and $R_{E\Delta h}^2$ statistics calculated for the longer sample period. We now see an even larger time variation of expected returns relative to the variation of observed returns. Retail properties and offices have the highest R_{Er}^2 statistics, at 29.2% and 27.8%, respectively. Apartment expected returns account for 19.2% of total apartment return variation, while industrial properties display the smallest R_{Er}^2 at 15.8%. Expected rent growth is substantially more predictable than expected returns over the longer sample period. As before, the $R_{E\Delta h}^2$ statistic is largest for offices at 42.9% and smallest for industrial properties at 22.1%.

3.4.2 Other Robustness Checks

Several other robustness checks are 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 return predictive regressions using only non-overlapping returns. The predictive power of the cap rates remains. In particular, we obtain bias-adjusted slope estimates that are similar to those previously reported and, in fact, the estimates and corresponding t_{DR} statistics at longer horizons are larger than those obtained when using overlapping returns. These results, however, should be interpreted with caution as the number of observations at longer horizons is rather small. Similarly, our results are unchanged if non-overlapping rent growth rates are used in the rent growth predictive regressions.

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 metropolitan areas. However, this homoscedasticity assumption may not be appealing as more populous metropolitan areas are generally more diverse, giving rise to more heterogeneity in the quality of a given property type. As a result, it is unlikely that, for example, the variance of residuals for Los Angeles will be the same as that of, say, Norfolk, Virginia. To address this concern, we use weighted least squares under the assumption that the heteroscedasticity in the residuals is proportional to a metropolitan area’s population. In particular, the weight assigned to a particular metropolitan area is given by its population divided by 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, expressions (3) and (4), by the square root of these computed weights. Interestingly, the bias-adjusted slope estimates now increase in magnitude but the corresponding t_{DR} statistics are very similar to those previously reported.

Expressions (3) and (4) can be thought of as cross-sectional regressions estimated once a quarter and 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 (2007)). In fact, the Fama-MacBeth approach produces very similar results when applied to our data. For example, in the case of apartment returns at a three-year horizon, we obtain a Fama-MacBeth estimate of 0.451 as opposed to the pooled estimate of 0.468. The corresponding Fama-MacBeth t statistic of 7.672, computed with Newey-West standard errors, is much larger than the t_{DR} statistic of 2.459 reported in Table 2. For retail property returns at the same horizon, we obtain a Fama-MacBeth estimate of 0.709 and a Newey and West (1987) t statistic of 7.730, versus a pooled estimate and t_{DR} statistic of 0.966 and 5.487, respectively, reported in Table 2. We obtain similar results for both return and rent growth predictive regressions at all horizons and across all property types, suggesting that the statistical significance of our small-sample results are conservatively stated.

We also conduct a Monte Carlo study to investigate the small sample properties of our estimators. In particular, we simulate the underlying structural model of expressions (9)-(12) using parameter estimates from Table 3 for various combinations of sample size and cross-sectional dimension. In unreported results, we confirm that the bias of the predictive regressions’ slope coefficients can be sizeable for sample sizes as small as thirty-six time series observations. However,

the bias disappears as the time series length increases. Next, we consider the cross-sectional dimension of our data. Experiments reveal that in comparison to the case of a single time series, the standard errors of the predictive regressions' slope coefficients are reduced by using cross-sectional information. The actual gains in efficiency depend on the correlations between the shocks to different metropolitan areas, with lower standard errors associated with uncorrelated as opposed to strongly correlated shocks.³¹

4 Cross-Sectional Differences in Predictive Regressions

To this point, our predictive regressions did not explicitly take into account the possibility that valuations of commercial properties located in different metropolitan areas might respond differently to underlying demographic and regional economic conditions. In other words, our estimation procedure implicitly assumed that the predictive ability of the cap rate to detect variations in future returns and growth in rents was independent of the location of the property. Unlike assets such as common stock or bonds, however, location is important in real estate markets. For example, Capozza, Hendershott, Mack, and Mayer (2002) find that house price dynamics vary with city size, population growth and density, as well as income growth and construction costs. Lamont and Stein (1999) conclude that house prices react more to city-specific shocks, such as shocks to per-capita income, in regions where homeowners are more leveraged. Gyourko, Mayer, and Sinai (2006) argue that the inelastic supply of land drives real estate prices in high-density areas. A related point is made by Mayer and Somerville (2000) who show that metropolitan areas with extensive regulation have significantly less construction activity and lower price elasticity relative to less regulated markets. Xing, Hartzell, and Godschalk (2006) provide a comprehensive review of this literature and provide indices which quantify land use regulations, such as development restrictions.³² In addition, Abraham and Hendershott (1996) document significant differences in the time-series properties of house prices in coastal *versus* inland cities. Given the importance of location to real estate, we turn our attention to understanding the extent to which geographic and demographic factors affect the time variation in commercial real estate expected returns and rent growth.

³¹Details are available upon request.

³²While most of the cited papers focus strictly on the residential real estate market, similar mechanisms are likely to be at play in the commercial real estate market.

4.1 Conditioning on Population Density and Land Use Restrictions

To investigate the role played by location specific factors in the time-series behavior of commercial real estate expected returns and expected rent growth, we condition our predictive regressions on population density and a measure of land use restrictions. Population density data for each of our sampled metropolitan areas is obtained from the 2000 U.S. Census. Land use restrictions are proxied by Xing, Hartzell, and Godschalk's (2006) Growth Management Tool Index which measures the stringency of growth management regulations in a given metropolitan area. The effectiveness of these measures to reduce the supply of land or prolong the approval process needed for real estate development was documented by Mayer and Somerville (2000) and Xing, Hartzell, and Godschalk (2006).

We sort our metropolitan areas according to their population density and divide the sorted areas in half to obtain a low-density sample versus a high-density sample. Separately, we also sort the metropolitan areas according to their Growth Management Tool Index value and divide the sorted areas in half to obtain a low-regulation sample versus a high-regulation sample. Approximately 48% of metropolitan areas which are classified as high-density are also high-regulation, while approximately 50% of the low-density areas are also classified as low-regulation areas. We then re-estimate the predictive regressions for each of the low-density, high-density, low-regulation, and high-regulation areas, separately. Conditioning on population density and land use restrictions allows us not only to investigate whether these variables play a role in the predictability but also to get a glimpse of what economic factors are behind the documented time variation in expected return and growth in rents.

The highlights of these estimation results are provided in Table 6. The estimated β coefficients, for brevity reported only at a forecast horizon of twelve quarters, are seen to be larger for the low-density areas than the high-density areas. The same results holds for land use regulation where the β coefficients estimated in the low-regulation areas are larger than those estimated in the high-regulation areas, except in the case of apartments. Despite the reduced number of data points in these sub-samples and the resultant lower power of our tests, we still see statistically significant evidence of in-sample return predictability at the twelve quarter horizon in both the low-density as well as low-regulation areas.³³ For the high-density or high-regulation areas, statistically significant

³³Inference is conducted using the same conservative double bootstrapping approach discussed above. Bootstrapping is particularly important in this instance since splitting the sample is likely to render large-sample

evidence of in-sample predictability at the twelve month horizon is seen only in the case of retail properties. By contrast, the time-variation in commercial real estate expected returns, measured by R_{Er}^2 , is most pronounced in the high-density or high-regulation areas. This is especially true in the case of offices.

The results of Table 6 also suggest that the in-sample evidence of rent growth predictability is drawn primarily from the high-density or high-regulation areas. The estimated λ coefficients at the twelve quarter forecast horizon tend to be larger in absolute value in these areas than the corresponding λ coefficients estimated in the low-density or low-regulation areas. Also, for a majority of property types, the estimated λ coefficients are of the correct negative sign in the high-density or high-regulation areas. However, only in the case of offices located in these areas do we have statistically significant in-sample evidence of rent growth predictability at the twelve quarter horizon. We also see that the time-variation in expected commercial real estate rent growth, measured by $R_{E\Delta h}^2$, is larger in the high-density or high-regulation areas, especially for apartments and offices.

These results confirm that location affects predictability patterns in commercial real estate markets. Evidence of return predictability is primarily drawn from locations characterized by lower population density and less stringent land use restrictions. By contrast, rent growth predictability is more likely observed in locations characterized by higher population density and more severe land use restrictions. The differences in predictability, especially in rent growth, are indicative that inelastic supply of land plays an important role in the documented time variations, which is consistent with Mayer and Somerville (2000) and Gyourko, Mayer, and Sinai (2006).

4.2 Additional Geographic, Demographic, and Local Economic Controls

In light of the extant evidence linking real estate valuations to underlying demographic, geographic and regional economic variables, we must ensure that cap rates are not merely proxying for these cross-sectional determinants as opposed to capturing time variation in prevailing economic conditions.³⁴ In addition, as we have documented, the cap rate is an imperfect predictor of the substantial time variation in commercial real estate expected returns and expected rent growth

inference imprecise.

³⁴Alternatively, without specifying the sources of these cross-sectional differences, we can also estimate these predictive regressions with fixed effects. Doing so, neither the estimated bias-adjusted slope coefficients nor the t_{DR} statistics change dramatically when relying on either the original or the extended sample.

rates. That being the case, this section also explores whether other economic variables can capture this time variation.

To test this “proxy” hypothesis, we capture differences across metropolitan areas by considering the following variables: population growth ($gpop_t$), the growth of per capita income ($ginc_t$), and the growth of employment ($gemp_t$), all of which are tabulated by the Bureau of Economic Analysis at an annual frequency. We also rely on the annual growth in construction costs (gcc_t) compiled by R.S. Means. These construction cost indices include material costs, installation costs, and a weighted average of total in place costs.³⁵ To proxy for the level of urbanization (Glaeser, Gyourko, and Saks (2004)), we also include, after lagging by two years, log population (pop_{t-2}), log per capita income (inc_{t-2}), log employment (emp_{t-2}), and log construction costs (cc_{t-2}).³⁶ We also include a dummy variable ($coast_t$) which equals one when the metropolitan area is in a coastal region.³⁷

A preliminary analysis of these economic control variables, however, reveals that many are highly correlated with one another.³⁸ This is not surprising because these variables all attempt to capture underlying economic and demographic conditions prevailing in a metropolitan area at a particular point in time. From a statistical perspective, such high correlations would decrease the power of our t -statistics.³⁹ To minimize multi-collinearity, we reduce the dimensionality of the economic control variables while at the same time succinctly summarizing their information content by performing a principal component analysis.⁴⁰ The principal components analysis reveals that three out of eight principal components account for more than 70% of the overall volatility. These three orthogonal extracted principal components are particularly correlated with the level

³⁵There are missing data for some metropolitan areas in our construction cost database. In these cases, we assigned the closest area for which data is available. In particular, we assigned to Oakland and San Jose the costs of San Francisco, to Nassau-Suffolk the costs of New York City while to West Palm Beach we assigned Miami costs. In cases where construction cost indices must be merged to correspond to a particular metropolitan area in our commercial real estate database, we do so by weighing the corresponding individual area indices by their respective populations.

³⁶We lag these level variables by two years to prevent a mechanical correlation with corresponding growth rates.

³⁷We 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 because all returns are computed in excess of the T-bill rate. Motivated by the results of Menzly, Santos, and Veronesi (2004), we also attempted to include a rent-to-income variable. However, this variable was highly correlated with some of the other controls and we did not include it in the regressions.

³⁸For example, the average cross-sectional correlation between per capita income and employment is about 0.97.

³⁹OLS regressions reveal that the inclusion of all the economic variables in the predictive regressions is associated with relatively high R^2 s, while the control variables have low t -statistics and are rarely found to be significant. These are clear symptoms of multi-collinearity in the regression specifications.

⁴⁰The coastal dummy is excluded. Another possibility is to select the variables according to their ability to improve the resultant regression’s R^2 . However, the set of variables so chosen is likely to vary across property types and would increase the risk of overfitting.

and growth in population and income as well as with the level of construction costs.

Therefore, we account for cross-sectional differences in the predictive relations by augmenting the regressions (3) and (4) as follows:

$$r_{i,t+1 \rightarrow t+k} = \alpha_k + \beta_k (cap_{i,t}) + \delta'_k Z_{i,t} + \varepsilon_{i,t+k} \quad (18)$$

$$\Delta h_{i,t+1 \rightarrow t+k} = \mu_k + \lambda_k (cap_{i,t}) + \eta'_k Z_{i,t} + v_{i,t+k} \quad (19)$$

where $Z_{i,t}$ includes observations on the three principal components of the economic variables as well as the coastal dummy.

If cap rates are proxying for differences across metropolitan areas and not capturing time variation in expected returns, then the inclusion of these cross-sectional proxies will lower the significance of the estimated cap rate coefficients while increasing the regressions' R^2 s. Similarly, under the proxy hypothesis, the exclusion of the cap rate from these regressions should not significantly alter the regressions' R^2 s.⁴¹

We estimate these regressions by GMM using the pooled sample of fifty-three metropolitan areas and imposing the present-value restriction on the cap rate coefficients β and λ .⁴² Since the economic control variables are only available at annual frequency, we aggregate returns and growth in rents over an annual period and use horizons of $k = 4, 8,$ and 12 quarters in the estimation.

Table 7 gives the resulting GMM estimates for the return predictive regression (r column) and the rent growth predictive regression (Δh column) at a horizon of $k = 12$ quarters.⁴³ For each property type, we consider two specifications. The first specification includes the cap rates, the principal components, and the coastal dummy. The second specification includes just the principal components and the coastal dummy. The purpose is to measure the marginal impact of including the cap rate in the predictive regressions. We also tabulate the OLS R^2_{adj} statistic corresponding to each specification.

Several conclusions emerge from the return predictive regressions. First, the cap rate

⁴¹The fixed effects 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 but without specifying their source. The drawback of this approach is that the dummy variables are simply too coarse to capture variation that can be better explained by correctly specifying the source of heterogeneity.

⁴²Since the value of the coastal dummy doesn't change over time, we also impose the constraints $\delta_k = k \cdot \delta_1$ and $\eta_k = k \cdot \eta_1$ on the dummy coefficient.

⁴³The results for $k = 4$ and 8 quarters are similar, and are omitted for brevity.

coefficients for apartments, industrial and retail properties remain positive and statistically significant. For example, the bias-adjusted coefficient for retail properties is 0.914 with a t_{DR} -statistic of 5.236. Second, the exclusion of the cap rate leads to a dramatic drop in the regression R_{adj}^2 s for these property types. Retail properties exhibit the largest decrease, from $R_{adj}^2 = 36.8\%$ in the first specification to only $R_{adj}^2 = 6.3\%$ when the cap rate is excluded. For these property types, cap rates appear to be capturing time varying effects even after accounting for cross-sectional differences across metropolitan areas. In the case of offices, however, the cap rate coefficient is not significant and its exclusion does not lead to a significant decrease in the regression R_{adj}^2 . Finally, the bias-corrected cap rate estimates in these predictive regressions are generally smaller than those in Table 2, except for apartments. This difference is likely due to our use of annual rather than quarterly data in these regressions.

Turning our attention to the rent growth predictive regressions, we see that the addition of the cross-sectional controls does not appreciably alter the cap rate's significance. As in the case of Table 2, the cap rate coefficient for offices is negative and is the largest in absolute value among all property types. Interestingly, the exclusion of the cap rate from these regressions does not result in a dramatic decrease in the R_{adj}^2 statistic as was the case for returns. We conclude then that the expected rent growth for all commercial property types is primarily determined by area-specific characteristics.

A closer examination of the economic control variables shows that they are statistically significant for most of the property types in both the returns as well as rent growth predictive regressions. In particular, either the first, second, or both principal components are significant at the 1% level or better. Interestingly, the signs of the principal components' coefficients remain the same across all specifications, suggesting that all property types are affected in the same direction by the underlying economic variables. The coastal dummy is also significant for all property types except retail.

Taken together, the evidence suggests that the cap rate is proxying for more than simple differences in expected returns across metropolitan areas. However, economic variables other than the cap rate are also important in predicting returns and, especially, rent growth in commercial real estate markets.

5 Commercial Real Estate in a Portfolio Allocation

A growing number of institutional investors, such as pension funds and endowment funds, include commercial real estate in their investment portfolios. We now take advantage of the time variation in expected commercial real estate returns to investigate the implications of adding commercial real estate to a portfolio already invested in the aggregate stock market and T-bills. Solving a dynamic asset allocation problem in which we rely upon the conditioning information contained in *both* the cap rate and the dividend yield provides a natural setting in which to gauge the economic importance of the time variation in expected commercial real estate returns.

As a preliminary, we document a number of cross-asset empirical relations prevailing between the stock market and the commercial real estate market at the aggregate level.⁴⁴ Previously we saw that the national cap rate and the stock market's dividend-price ratio are highly correlated (Figure 1, Section 2.2). Since the cap rate predicts commercial real estate returns while the aggregate dividend yield captures variation in future stock market returns, it is natural to ask whether the cap rate captures fluctuations in future stock market returns and, alternatively, whether the aggregate dividend yield forecasts commercial real estate returns. To answer these questions, we regress six-month ahead excess stock returns, measured by the return of the CRSP value-weighted index less the corresponding T-bill rate, on our national cap rate series over the 1985 to 2002 sample period. The estimated slope coefficient of 0.778 is marginally significant with a bootstrapped t -statistic of 1.624. Conversely, the stock market's log dividend-price ratio is negatively related to six-month ahead excess commercial real estate returns on a national basis, where the national commercial real estate market's return is measured by the simple average of the national returns of each of the four property types. The estimated slope coefficient over the 1985 to 2002 sample period is -0.013 with a bootstrapped t -statistic of -0.8 . Finally, the correlation between the realized returns of the two assets is 0.155 over the 1985 to 2002 sample period. The stock market series is more volatile, with an annualized standard deviation of approximately 15 percent, compared to an annualized standard deviation of only 3.5 percent for the national commercial real estate series.

We use the parametric portfolio approach of Brandt and Santa-Clara (2006) to exploit the conditioning information of the cap rate and the dividend-price ratio in a dynamic portfolio allocation across the aggregate stock market, commercial real estate, and T-bills. This approach

⁴⁴As in Section 2.2, we construct the national series as simple average of the property-type series, calculated as population-weighted average of the corresponding variable across metropolitan areas.

expands the set of assets to include conditioning portfolios which invest in an available asset an amount proportional to the underlying conditioning variables. The solution to the dynamic portfolio problem is obtained by solving a static portfolio problem where the set of available assets also includes these simple dynamic trading strategies. In the absence of conditioning variables, the problem reduces to the traditional, static Markowitz optimization. An advantage of Brandt and Santa-Clara (2006)'s approach is that the solution of the dynamic portfolio problem is obtained using ordinary least squares and standard sampling theory can be used to carry out hypothesis tests on the resultant portfolio weights.

Following Brandt and Santa-Clara (2006), we assume that the time-varying portfolio weights w_t of the N available assets are related to standardized conditioning variables z_t (a $K \times 1$ vector) by a linear parametric form $w_t = \theta z_t$, where θ is a $N \times K$ matrix of parameters to be estimated. It is easy to demonstrate that solving the dynamic portfolio problem with the parameterized portfolio weights is mathematically equivalent to solving the static optimization problem

$$\max_{\tilde{w}} E_t \left[\tilde{w}' \tilde{r}_{t+1} - \frac{\gamma}{2} \tilde{w}' \tilde{r}_{t+1} \tilde{r}_{t+1}' \tilde{w} \right] \quad (20)$$

where γ measures the relative risk aversion of the representative investor, $\tilde{r}_{t+1} \equiv z_t \otimes r_{t+1}$ and \tilde{w} is a vectorized version of θ , $\tilde{w} = \text{vec}(\theta)$. Like Brandt and Santa-Clara (2006), we use a quadratic utility function because of its simplicity and also because it can be viewed as a second-order approximation of the investor's true utility function.

Before implementing the optimization, transaction costs incurred in the buying and selling of commercial real estate must be accounted for. Unlike common stocks, which are traded in liquid markets and transaction costs are relatively low, this is not the case for commercial real estate where round-trip transaction costs can be as high as 5 percent (Geltner and Miller (2000)). Accounting for these costs significantly complicates the optimal dynamic allocation problem (e.g., Magill and Constantinides (1976) and Leland (2000)). This being the case, we adapt the approach of Brandt, Santa-Clara, and Valkanov (2009) to our problem. To do so, in the absence of conditioning variables, we apply a simple round-trip proportional-cost adjustment of 5 percent on an annual basis to commercial real estate expected returns. By contrast, in the presence of the conditioning variables and time-varying portfolio weights, we impose these transaction costs based on turnover, that is, the absolute difference in portfolio weights between times t and $t+1$ and then solve the optimization problem.

Our focus is on the estimation of θ in the unconditional versus conditional specifications. The unconditional case corresponds to the static mean-variance problem, or $z_t = [1]$. In the conditional case, z_t includes combinations of the log dividend-price ratio and the log cap rate motivated by the previous evidence that they capture time-variation in the conditional means of the returns to commercial real estate and common stock. When conditioning on both the cap rate and the dividend-price ratio, we have $z_t = [1, dp_t, cap_t]$ and θ is a 2×3 matrix. To reduce estimation error, we measure all portfolio inputs over the longer sample period 1986:Q2 - 2002:Q4. Bootstrapped t -statistics are displayed in parentheses below the estimates. Following Brandt and Santa-Clara (2006) and Brandt, Santa-Clara, and Valkanov (2009), we set $\gamma = 5$. The results are presented in Table 8. In particular, summary statistics for the optimal portfolio corresponding to each strategy are provided in the last row of each column.

The first column of Table 8 displays the estimated allocation between the stock market portfolio, commercial real estate, and T-bills for the case of no conditioning variables. This three-asset, static allocation (or $N = 3$ and $K = 1$) places 58.2 percent of the portfolio into the aggregate stock market, 16.7 percent into commercial real estate, and the balance of 25.1 percent into T-bills. The annualized Sharpe ratio in this static case is 0.446.

The second column reports the results from conditioning on fluctuations in the log dividend-price ratio in the portfolio allocation problem ($K = 2$). Since the variables in z_t have been standardized, we can interpret the constant term in the conditioning problem as the time-series average of the weights in a particular asset. This implies that, relative to the static strategy, the stock market portfolio weight has, on average, decreased to 53 percent while the allocation to commercial real estate has increased to 29.1 percent. We also see that the log dividend-price ratio is estimated to have a positive coefficient with respect to the common stock allocation and a negative coefficient with respect to the commercial real estate allocation, and is consistent with the cross-asset predictability results presented earlier. In other words, in periods of higher than average log dividend-price ratios, investors should hold more stocks and less commercial real estate, all else being equal. When conditioning on the dividend-price ratio, we observe an increase in the Sharpe ratio from 0.446 to 0.677, yielding a certainty equivalent return of 3.0 percent, relative to the static strategy. These performance gains are, economically speaking, significant.

The third column of Table 8 displays the results of adding the log cap rate to the log dividend-price ratio as conditioning variables in the dynamic asset allocation problem ($K = 3$). Including the

cap rate significantly affects the portfolio allocation. In particular, the average allocation to common stock now increases to 66.4 percent while commercial real estate's average allocation is reduced to 18.0 percent. The log cap rate is estimated to have positive coefficients with respect to both common stock and commercial real estate allocations. That is, in periods of higher than average cap rates, the allocation into common stock and commercial real estate should increase, all else being equal. From this perspective, the cap rate contains information which differs from that contained in the dividend-price ratio which positively impacts the allocation of common stock but negatively impacts the allocation of commercial real estate. The Sharpe ratio of this dynamic strategy is 0.976, which is remarkably high when compared to the previous two strategies. The certainty equivalent return increases to 6.6 percent annually, 3.6 percent higher than the corresponding value when conditioning just on the dividend-price ratio. Some of these gains are undoubtedly attributable to in-sample fitting rather than to a true out-of-sample increase in performance. Also, from a statistical perspective, the average weights, especially the average commercial real estate allocation, have large standard errors reflecting the fact that the estimation is based on a small number of time-series observations. Despite these data limitations, both conditioning variables appear to play a significant role in the dynamic portfolio strategy.

Figure 4 plots the time-varying portfolio weights over the 1986:Q2 - 2002:Q4 sample period for the dynamic portfolio strategy which conditions on both the cap rate and dividend yield versus the static portfolio strategy which does not. These weights are obtained by inputting the estimated θ parameters from Table 8 into the parameterized weights $w_t = \theta z_t$ for the observed vector of conditioning variables z_t . The top Panel in Figure 4 displays the allocation into the aggregate stock market while the bottom Panel displays the allocation into commercial real estate. In each Panel, the dotted line represents the portfolio weight of the static portfolio strategy, which corresponds to the unconditional case in Table 8. The weights of the dynamic strategy, conditioned on the dividend-price ratio and the cap rate, are given by the solid line and can be seen to fluctuate over the sample period to exploit the time-variation in z_t . For the stock market, in the first part of the sample, the weights are relatively stable and perhaps slightly lower than what would be allocated to this asset under the unconditional strategy. The allocation into common stock increases during the mid 1990s, in anticipation of the stock market's improved performance towards the end of that decade, and turns negative in the last portion of our sample, reflecting the stock market's poor performance during the early 2000s. For commercial real estate, the weights are negative in the first part of the sample, corresponding to the poor investment opportunities in that market in the

late 1980s and early 1990s. From 1993 onwards, however, the allocation to commercial real estate steadily increases in order to take advantage of the improved performance of this asset class in the late 1990s. Interestingly, the allocation into commercial real estate peaks in the first two quarters of the year 2000 and then decreases significantly, reflecting the high valuations and lower than average cap rates prevailing during that period.

Two final remarks about the dynamic portfolio results are in order. The time-varying portfolio weights are persistent, which is to be expected since they are linear combinations of the persistent variables in z_t . From a portfolio allocation perspective, this persistence facilitates trading and mitigates transaction costs which, in our case, are quite significant. Also, a glance at Figure 4 reveals a substantial short position in commercial real estate during the early part of the sample period. A short position in commercial real estate is difficult to implement.⁴⁵ To address this concern, we follow Campbell and Thompson (2008) and impose the realistic constraint of preventing the portfolio manager from shorting commercial real estate. Instead, when the dynamic portfolio strategy requires such a short position, all of the funds are invested in T-bills. With this binding short sale constraint, the resultant portfolio has a Sharpe Ratio of 1.04 which implies an even higher certainty equivalent return of 6.85 percent. This result is due to the fact that lower transaction costs are now incurred. Therefore, adding commercial real estate to a portfolio position in common stock and T-bills is beneficial whether or not short-selling constraints are imposed.

6 Conclusions

This paper documents that commercial real estate returns and rent growth rates are time-varying. The cap rate, the equivalent of the dividend-price ratio in commercial real estate markets, captures time variation in expected returns but not expected rent growth rates of apartments as well as retail and industrial properties. For these property types, the time variation in expected returns generates economically significant movements in corresponding property prices. By contrast, offices cap rates are not able to capture the time variation in expected returns but somewhat track expected office rent growth rates.

⁴⁵Our analysis is subject to a number of other caveats. For example, it assumes that the commercial real estate position is itself diversified both across property types as well as by location. To the extent that commercial real estate investments tend to be specialized by either property type or by location, the resultant investments are subject to idiosyncratic risk which we do not account for. We also assume that commercial real estate positions are divisible as opposed to being only available as whole buildings.

Commercial real estate markets offer a natural setting in which to demonstrate that the predictability of expected returns by scaled cash flow measures, such as the cap rate, is sensitive to the properties of cash flow growth rates as suggested earlier by Campbell and Shiller (1988b) and more recently argued by Lettau and Ludvigson (2005) and Menzly, Santos, and Veronesi (2004). In particular, we establish that while the expected returns of the four commercial property types have similar exposures to macroeconomic variables, their rent growth rates differ in their correlations with expected returns. As a result, in the case of offices, whose rent growth rate is the most highly correlated with expected returns, the cap rate is not able to forecast expected returns even though expected returns on offices are themselves time-varying.

Future work in this area should focus on identifying other important determinants of expected returns and expected rent growth rates in commercial real estate markets. A step in that direction was the provided evidence that population density, land use regulation, and perhaps other location-specific variables might play a crucial economic role. Ideally, this effort should start from economic primitives to derive expected returns and expected rent growth rates endogenously. Our paper can serve as a useful resource in this effort by providing diagnostics describing the properties of expected returns and expected rent growth rates for various property types.

Appendix

A List of Metropolitan Areas

The cap rates and returns of the following fifty-three metropolitan areas are available at quarterly frequency for the 1994:Q2 - 2003:Q1 period: Atlanta* (GA), Austin (TX), Baltimore* (MD), Birmingham (AL), Boston* (MA), Central New Jersey (NJ), Charlotte* (NC), Chicago* (IL), Cincinnati (OH), Cleveland (OH), Columbus (OH), Dallas - Ft. Worth* (TX), Denver* (CO), Detroit (MI), Fort Lauderdale (FL), Greensboro - Winston -Salem (NC), Hartford (CT), Houston* (TX), Indianapolis (IN), Jacksonville (FL), Kansas City (MO), Las Vegas (NV), Los Angeles* (CA), Memphis (TN), Miami (FL), Milwaukee (WI), Minneapolis - St. Paul* (MN), Nashville (TN), Nassau - Suffolk (NY), New Orleans (LA), Norfolk (VA), Northern New Jersey (NJ), Oakland East Bay (CA), Oklahoma City (OK), Orange County* (CA), Orlando* (FL), Philadelphia* (PA), Phoenix* (AZ), Pittsburgh (PA), Portland (OR), Raleigh - Durham (NC), Riverside - S. Bernardino* (CA), Sacramento* (CA), Salt Lake City (UT), San Antonio (TX), San Diego* (CA), San Francisco* (CA), San Jose (CA), Seattle* (WA), St. Louis (MO), Tampa - St. Petersburg* (FL), Washington D.C.* , West Palm Beach (FL). An asterisk denotes the twenty-one areas whose data are available at semi-annual frequency for the 1985:Q2 - 2002:Q4 period.

B From Structural to Reduced Form

In this section we provide the main derivations necessary to establish the link between the structural model

$$\begin{aligned}\Delta h_{t+1} &= g + \tau x_t + y_t + \xi_{t+1}^h \\ r_{t+1} &= r + x_t + \xi_{t+1}^r \\ y_{t+1} &= \psi y_t + \xi_{t+1}^x \\ x_{t+1} &= \phi x_t + \xi_{t+1}^y\end{aligned}$$

and its reduced form

$$\begin{aligned} r_{t+1} &= \alpha + \beta(\text{cap}_t) + \varepsilon_{t+1}^r \\ \Delta h_{t+1} &= \mu + \lambda(\text{cap}_t) + \varepsilon_{t+1}^h \\ \text{cap}_{t+1} - c &= \phi(\text{cap}_t - c) + \varepsilon_{t+1}^c \end{aligned}$$

under the following assumptions on the covariance structure of the structural shocks: $Cov(\xi_{t+1}^y, \xi_{t+j}^x) = 0 \forall j$, $Cov(\xi_{t+1}^h, \xi_{t+j}^x) = 0 \forall j$, $Cov(\xi_{t+1}^h, \xi_{t+j}^y) = 0 \forall j \neq 1$, and $Cov(\xi_{t+1}^h, \xi_{t+1}^y) = \vartheta$.

The AR(1) structure of the log cap rate

By iterating equation (14), using the AR(1) structure of x and y and defining $c \equiv (r - g)/(1 - \rho)$, we get:

$$\begin{aligned} \text{cap}_{t+1} - c &= \frac{1}{1 - \rho\phi}((1 - \tau)x_{t+1} - y_{t+1}) \\ &= \frac{\phi}{1 - \rho\phi}((1 - \tau)x_t - y_t) + \frac{(1 - \tau)\xi_{t+1}^x - \xi_{t+1}^y}{1 - \rho\phi} \\ &= \phi(\text{cap}_t - c) + \varepsilon_{t+1}^c \end{aligned}$$

where the shock on the log cap rate is defined as:

$$\varepsilon_{t+1}^c = \frac{(1 - \tau)\xi_{t+1}^x - \xi_{t+1}^y}{1 - \rho\phi}.$$

Slope coefficients in the predictive regressions

We can write the slope coefficients of the one-period predictive regressions in reduced form in terms of the structural parameters as

$$\begin{aligned} \beta &= \frac{Cov(r_{t+1}, \text{cap}_t)}{Var(\text{cap}_t)} = \frac{(1 - \rho\phi)(1 - \tau)\sigma_{\xi_x}^2}{(1 - \tau)^2\sigma_{\xi_x}^2 + \sigma_{\xi_y}^2} \\ \lambda &= \frac{Cov(\Delta h_{t+1}, \text{cap}_t)}{Var(\text{cap}_t)} = \frac{-(1 - \rho\phi) [\tau(\tau - 1)\sigma_{\xi_x}^2 + \sigma_{\xi_y}^2]}{(1 - \tau)^2\sigma_{\xi_x}^2 + \sigma_{\xi_y}^2}. \end{aligned}$$

Proof for β : From the AR(1) structure of the cap rate,

$$Var(cap_t) = \frac{(1-\tau)^2\sigma_{\xi^x}^2 + \sigma_{\xi^y}^2}{(1-\rho\phi)^2} \cdot \frac{1}{1-\phi^2} \equiv V.$$

Also,

$$\begin{aligned} Cov(r_{t+1}, cap_t) &= Cov(x_t + \xi_{t+1}^r, cap_t) = Cov\left(\frac{(1-\rho\phi)cap_t + y_t}{1-\tau} + \xi_{t+1}^r, cap_t\right) \\ &= \frac{1-\rho\phi}{1-\tau}V - \frac{1}{(1-\rho\phi)(1-\tau)}\frac{\sigma_{\xi^y}^2}{1-\phi^2}. \end{aligned}$$

Therefore,

$$\beta = \frac{\frac{1-\rho\phi}{1-\tau}V - \frac{1}{(1-\rho\phi)(1-\tau)}\frac{\sigma_{\xi^y}^2}{1-\phi^2}}{V}$$

which, after simplification, gives the desired result.

Proof for λ : Using the result above and the fact that

$$\begin{aligned} Cov(\Delta h_{t+1}, cap_t) &= Cov\left(\tau x_t + y_t + \xi_{t+1}^h, \frac{(1-\tau)x_t - y_t}{1-\rho\phi}\right) \\ &= \frac{\tau(1-\tau)}{1-\rho\phi}Var(x_t) - \frac{1}{1-\rho\phi}Var(y_t) \\ &= \frac{\tau(1-\tau)}{1-\rho\phi}\frac{\sigma_{\xi^x}^2}{1-\phi^2} - \frac{1}{1-\rho\phi}\frac{\sigma_{\xi^y}^2}{1-\phi^2} \end{aligned}$$

we obtain

$$\lambda = \frac{\frac{\tau(1-\tau)}{1-\rho\phi}\frac{\sigma_{\xi^x}^2}{1-\phi^2} - \frac{1}{1-\rho\phi}\frac{\sigma_{\xi^y}^2}{1-\phi^2}}{\frac{(1-\tau)^2\sigma_{\xi^x}^2 + \sigma_{\xi^y}^2}{(1-\rho\phi)^2} \cdot \frac{1}{1-\phi^2}}$$

which, after simplification, gives the desired result.

Innovations in the predictive regressions

By comparing the structural and the reduced form models, as well as using the above definitions of the slope coefficients together with the expression for ξ_{t+1}^r from the Campbell (1991) decomposition,

we can express the residuals of the predictive regressions as:

$$\begin{aligned}\varepsilon_{t+1}^r &= \xi_{t+1}^h + x_t \left(\frac{\tau\beta - \lambda}{1 - \rho\phi} \right) + y_t \left(\frac{\beta}{1 - \rho\phi} \right) + \rho \frac{(\tau - 1)\xi_{t+1}^x + \xi_{t+1}^y}{1 - \rho\phi} \\ \varepsilon_{t+1}^h &= \xi_{t+1}^h + x_t \left(\frac{\tau\beta - \lambda}{1 - \rho\phi} \right) + y_t \left(\frac{\beta}{1 - \rho\phi} \right).\end{aligned}$$

Moreover, the assumptions on the variance-covariance structure of the structural form innovations imply the following expressions for the variances and covariance of the two shocks:

$$\begin{aligned}\sigma_{\varepsilon^h}^2 &= \sigma_{\xi^h}^2 + \frac{\sigma_{\xi^x}^2}{1 - \phi^2} \cdot \left(\frac{\tau\beta - \lambda}{1 - \rho\phi} \right)^2 + \frac{\sigma_{\xi^y}^2}{1 - \phi^2} \cdot \left(\frac{\beta}{1 - \rho\phi} \right)^2 \\ \sigma_{\varepsilon^r}^2 &= \sigma_{\xi^h}^2 + \frac{\sigma_{\xi^x}^2}{1 - \phi^2} \cdot \left(\frac{\tau\beta - \lambda}{1 - \rho\phi} \right)^2 + \frac{\sigma_{\xi^y}^2}{1 - \phi^2} \cdot \left(\frac{\beta}{1 - \rho\phi} \right)^2 + \frac{\rho^2(1 - \tau)^2}{(1 - \rho\phi)^2} \sigma_{\xi^x}^2 + \frac{\rho^2}{(1 - \rho\phi)^2} \sigma_{\xi^y}^2 + \frac{2\rho}{1 - \rho\phi} \vartheta \\ \sigma_{\varepsilon^r, \varepsilon^h} &= \sigma_{\xi^h}^2 + \frac{\sigma_{\xi^x}^2}{1 - \phi^2} \cdot \left(\frac{\tau\beta - \lambda}{1 - \rho\phi} \right)^2 + \frac{\sigma_{\xi^y}^2}{1 - \phi^2} \cdot \left(\frac{\beta}{1 - \rho\phi} \right)^2 + \frac{\rho}{1 - \rho\phi} \vartheta.\end{aligned}$$

C Parameters Identification

The structural parameter vector consists of six elements, $\Psi = [\phi, \tau, \sigma_{\xi^x}, \sigma_{\xi^y}, \sigma_{\xi^h}, \vartheta]$. The vector of estimated reduced form parameters is $\Theta = [\phi, \beta, \lambda, \Sigma_\varepsilon]$. The covariance matrix of reduced form residuals Σ_ε is a symmetric 3×3 matrix so it has six unique elements. However, substituting the expression for β and λ in the present value constraint, we can rewrite the latter as a constraint on the reduced form errors, $\rho\varepsilon^c = \varepsilon^h - \varepsilon^r$. This implies that we have just three unique elements in Σ_ε to be used for structural parameters identification. We choose these elements to be the variance of the return innovation, $\sigma_{\varepsilon^r}^2$, the variance of the rent growth equation innovation, $\sigma_{\varepsilon^h}^2$, and their covariance $\sigma_{\varepsilon^r, \varepsilon^h}$. Their expressions can be derived using the above assumptions on the covariance structure of the structural model shocks. As a result, we are left with the following system of five

equations in six unknowns (structural parameters):

$$\left\{ \begin{array}{l} \beta = \frac{(1-\rho\phi)(1-\tau)\sigma_{\xi^x}^2}{(1-\tau)^2\sigma_{\xi^x}^2 + \sigma_{\xi^y}^2} \\ \beta - \lambda = 1 - \rho\phi \\ \sigma_{\epsilon^h}^2 = \sigma_{\xi^h}^2 + \frac{\sigma_{\xi^x}^2}{1-\phi^2} \cdot \left(\frac{\tau\beta-\lambda}{1-\rho\phi}\right)^2 + \frac{\sigma_{\xi^y}^2}{1-\phi^2} \cdot \left(\frac{\beta}{1-\rho\phi}\right)^2 \\ \sigma_{\epsilon^r}^2 = \sigma_{\xi^h}^2 + \frac{\sigma_{\xi^x}^2}{1-\phi^2} \cdot \left(\frac{\tau\beta-\lambda}{1-\rho\phi}\right)^2 + \frac{\sigma_{\xi^y}^2}{1-\phi^2} \cdot \left(\frac{\beta}{1-\rho\phi}\right)^2 + \frac{\rho^2(1-\tau)^2}{(1-\rho\phi)^2}\sigma_{\xi^x}^2 + \frac{\rho^2}{(1-\rho\phi)^2}\sigma_{\xi^y}^2 + \frac{2\rho}{1-\rho\phi}\vartheta \\ \sigma_{\epsilon^r, \epsilon^h} = \sigma_{\xi^h}^2 + \frac{\sigma_{\xi^x}^2}{1-\phi^2} \cdot \left(\frac{\tau\beta-\lambda}{1-\rho\phi}\right)^2 + \frac{\sigma_{\xi^y}^2}{1-\phi^2} \cdot \left(\frac{\beta}{1-\rho\phi}\right)^2 + \frac{\rho}{1-\rho\phi}\vartheta. \end{array} \right.$$

Note that the expression for λ does not provide any additional information as it follows directly from the first two expressions. To derive the structural parameters from the estimated vector Θ we therefore have to impose an additional identification restriction. We obtain this restriction from the covariance between r_t and Δh_{t+1} which can be written in terms of the structural parameters as:

$$\text{Cov}(r_t, \Delta h_{t+1}) = \phi\tau \frac{\sigma_{\xi^x}^2}{1-\phi^2} + \tau(\tau-1) \frac{\rho}{1-\rho\phi} \sigma_{\xi^x}^2 + \frac{\rho}{1-\rho\phi} \sigma_{\xi^y}^2 + \vartheta.$$

Using this expression, our system becomes exactly identified and we are able to recover the structural parameters from the reduced form estimates.⁴⁶

D Derivatives of the Slope Coefficients

As we have seen in Section 2.3, we can write the predictive regression coefficients β and λ as a function of the underlying structural parameters

$$\begin{aligned} \beta &= \frac{(1-\rho\phi)}{(1-\tau) + v \frac{1}{1-\tau}} \\ \lambda &= \frac{-(1-\rho\phi) [\tau(\tau-1) + v]}{(1-\tau)^2 + v}. \end{aligned}$$

⁴⁶Alternatively, we could obtain the additional restriction from the slope coefficient in the regression of Δh_{t+1} on r_t . We verify that our results are not sensitive to this choice of the restriction.

Here, we characterize the behavior of these coefficients further by looking at their derivatives with respect to the two structural parameters τ and v . Throughout this section, we keep the values of ϕ and ρ fixed at 0.95 and 0.98 respectively, which imply that $(1 - \rho\phi) > 0$.

The derivatives of β and λ with respect to τ are:

$$\begin{aligned}\frac{\partial\beta}{\partial\tau} &= \frac{(1 - \rho\phi) [(1 - \tau)^2 - v]}{\left[(1 - \tau) + \frac{v}{1 - \tau}\right]^2 (1 - \tau)^2} \\ \frac{\partial\lambda}{\partial\tau} &= \frac{(1 - \rho\phi) [(1 - \tau)^2 - v]}{[(1 - \tau)^2 + v]^2}.\end{aligned}$$

As we can see, the sign of both derivative depends on the same expression $[(1 - \tau)^2 - v]$. The coefficients are increasing and then decreasing in τ , with a maximum value attained at $\tau = 1 - \sqrt{v}$.⁴⁷

For λ , it is particularly interesting to combine the sign of its derivative with the sign of the coefficient. From the expression above, we can see that λ is zero for $\tau_a = 0.5 - \sqrt{0.25 - v}$ and $\tau_b = 0.5 + \sqrt{0.25 - v}$, the roots of the polynomial $(-\tau^2 + \tau - v)$. Given that λ has a unique maximum, we can characterize its sign for combinations of the structural parameters (τ, v) regardless the value of ϕ and ρ . That is, λ is positive for values of $\tau \in [\tau_a, \tau_b]$ and negative for values of τ outside this interval. For example, for $v = 0.13$ we have that λ is positive for values of $\tau \in [0.1536, 0.8464]$ and reaches a maximum of 0.0267 ($\tau = 0.6394$). For the same value of v , β is positive for all values of τ and reaches a maximum of 0.0957. As expected, for $v = 0.25$ we have that $\tau_a = \tau_b = 0$ and λ is always non-positive.

The derivatives with respect to v are:

$$\begin{aligned}\frac{\partial\beta}{\partial v} &= \frac{-(1 - \rho\phi)}{\left[(1 - \tau) + \frac{v}{1 - \tau}\right]^2 (1 - \tau)} \\ \frac{\partial\lambda}{\partial v} &= \frac{-(1 - \rho\phi)(1 - \tau)}{[(1 - \tau)^2 + v]^2}.\end{aligned}$$

As we can see, the derivatives are negative provided $(1 - \rho\phi) > 0$, which is our maintained assumption. Thus, both β and λ are decreasing function of v . Intuitively, v represents a noise-to-signal ratio in the return regression and a signal-to-noise ratio in the rent growth regression. A larger value of v then reduces return predictability (smaller β) and increases rent growth predictability

⁴⁷The other root of the polynomial, $\tau = 1 + \sqrt{v}$ corresponds to a value of τ greater than unity and is not considered.

(larger λ in absolute value).

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Table 1: Summary statistics

This table reports summary statistics for excess returns (r), rent growth (Δh), and cap rates (cap) for the four commercial real estate property types. The table displays the mean (μ), the standard deviation (σ), and the first order (ρ_1) and fourth order (ρ_4) autocorrelation coefficients, calculated as averages across metropolitan areas. The table also shows the t -test for the null hypothesis of zero first-order autocorrelation for the excess returns and rent growth series, and the ADF test for the null hypothesis of unit root for the cap rate series. Statistical significance at the 5% and 1% level is denoted by superscripts a and b , respectively. The sample is quarterly observations of 53 areas from 1994:Q2 to 2003:Q1.

	Apartments					Industrial				
	μ	σ	ρ_1	ρ_4	t/ADF	μ	σ	ρ_1	ρ_4	t/ADF
r	0.095	0.061	0.042	0.045	-0.023	0.078	0.053	0.040	-0.005	-0.135
Δh	0.037	0.044	0.092	0.115	0.659	0.024	0.040	0.049	0.078	0.369
cap	0.089	0.009	0.846 ^b	0.544 ^b	-1.560	0.092	0.006	0.759 ^b	0.319 ^a	-2.176
	Retail					Offices				
	μ	σ	ρ_1	ρ_4	t/ADF	μ	σ	ρ_1	ρ_4	t/ADF
r	0.075	0.037	0.178	-0.003	1.121	0.073	0.050	0.274	0.018	1.522
Δh	0.021	0.032	0.045	0.040	0.404	0.025	0.047	0.149	0.059	1.126
cap	0.093	0.006	0.836 ^b	0.446 ^b	-1.647	0.091	0.007	0.845 ^b	0.415 ^b	-1.680

Table 2: GMM Forecasting Regressions of Returns and Rent Growth on Log Cap Rate

This table reports the two-stage GMM estimates for the regression of excess returns and rent growth between $t + 1$ and $t + k$ on the log cap rate at time t for the four commercial real estate property types. The moments are the OLS orthogonality conditions. In the system, horizons of $k = (1, 4, 8, 12)$ quarters are used. The estimation imposes the present value constraint (equation 17) and the short-long horizon relationship (equation 8) on the slope coefficients. The first stage weighting matrix is the identity matrix. The first stage estimator is then used to construct the optimal weighting matrix for the second stage, based on the Newey and West (1987) estimator with $q = 4$ lags. In the table, $\hat{\beta}_k^{adj}$ and $\hat{\lambda}_k^{adj}$ denote the bias-adjusted slope coefficients for the excess returns and rent growth regressions, respectively. The t -ratios t_{DR} are obtained using the double-resampling procedure described in Section 3.1. Statistical significance at the 5% and 1% level, evaluated using the empirical distribution from the double-resampling procedure, is denoted by superscripts a and b , respectively. The long-horizon coefficients β_k ($k \geq 4$) are obtained as $\beta_1(1 - \phi^k)/(1 - \phi)$, using the implied ϕ from the present value constraint. Their standard errors are then calculated using the delta method. The table also shows the R^2 for the OLS regressions of log cap rates on future returns (R_r^2) and on future rent growth ($R_{\Delta h}^2$), estimated separately. The sample is quarterly observations of 53 areas from 1994:Q2 to 2003:Q1.

Apartments							Industrial					
k	$\hat{\beta}_{adj}$	t_{DR}	R_r^2	$\hat{\lambda}_{adj}$	t_{DR}	$R_{\Delta h}^2$	$\hat{\beta}_{adj}$	t_{DR}	R_r^2	$\hat{\lambda}_{adj}$	t_{DR}	$R_{\Delta h}^2$
1	0.045 ^a	2.215	0.041	-0.003	-0.218	0.004	0.066 ^b	2.620	0.036	0.001	0.050	0.002
4	0.174 ^a	2.283	0.103	-0.013	-0.218	0.010	0.247 ^b	2.710	0.117	0.004	0.050	0.000
8	0.330 ^a	2.373	0.163	-0.024	-0.218	0.017	0.454 ^b	2.818	0.154	0.007	0.050	0.009
12	0.468 ^a	2.459	0.174	-0.035	-0.218	0.019	0.626 ^b	2.910	0.147	0.010	0.050	0.009
Retail						Offices						
k	$\hat{\beta}_{adj}$	t_{DR}	R_r^2	$\hat{\lambda}_{adj}$	t_{DR}	$R_{\Delta h}^2$	$\hat{\beta}_{adj}$	t_{DR}	R_r^2	$\hat{\lambda}_{adj}$	t_{DR}	$R_{\Delta h}^2$
1	0.111 ^b	4.746	0.030	0.030	1.474	0.002	0.027	1.119	0.006	-0.047 ^a	-2.263	0.007
4	0.405 ^b	5.018	0.123	0.109	1.465	0.000	0.101	1.132	0.028	-0.174 ^a	-2.261	0.005
8	0.720 ^b	5.305	0.223	0.193	1.451	0.016	0.182	1.149	0.039	-0.313 ^a	-2.252	0.006
12	0.966 ^b	5.487	0.271	0.259	1.437	0.031	0.247	1.163	0.027	-0.424 ^a	-2.238	0.023

Table 3: Structural Parameters

Panel A of this table reports the underlying structural parameters of the model described in equations (9)-(12) for the four commercial real estate property types. The identification is obtained from the GMM estimates of Table 2, using the moment conditions as described in Appendix C. Panel B shows the implied annualized standard deviation of expected returns ($\text{std}(E_t r_{t+1})$), expected rent growth ($\text{std}(E_t \Delta h_{t+1})$), returns ($\text{std}(r_{t+1})$), and rent growth ($\text{std}(\Delta h_{t+1})$). Panel C shows the variance of expected returns as a fraction of total return variance (denoted by R_{Er}^2) and the variance of expected rent growth as a fraction of total rent growth variance ($R_{E\Delta h}^2$). Volatilities and covariances are expressed in annual terms. The sample is quarterly observations of 53 areas from 1994:Q2 to 2003:Q1.

Panel A				
	Apartments	Industrial	Retail	Offices
ϕ	0.972	0.956	0.939	0.946
$\sigma_{\xi^x} \times 10^2$	0.493	0.379	0.667	0.806
$\sigma_{\xi^y} \times 10^2$	0.249	0.164	0.241	0.343
$\sigma_{\xi^h} \times 10^2$	4.211	4.504	3.632	5.128
τ	0.648	0.275	0.694	0.932
$\vartheta \times 10^4$	-0.147	-0.241	-0.509	-0.596

Panel B				
	Apartments	Industrial	Retail	Offices
$\sigma_{\xi^r} \times 10^2$	6.982	6.026	3.924	5.608
$v = \sigma_{\xi^y}^2 / \sigma_{\xi^x}^2$	0.254	0.187	0.130	0.181
$\text{std}(r_{t+1})$	0.073	0.062	0.044	0.061
$\text{std}(E_t r_{t+1})$	0.021	0.013	0.019	0.025
$\text{std}(\Delta h_{t+1})$	0.045	0.046	0.039	0.057
$\text{std}(E_t \Delta h_{t+1})$	0.017	0.007	0.015	0.025

Panel C				
	Apartments	Industrial	Retail	Offices
R_{Er}^2	0.082	0.044	0.197	0.163
$R_{E\Delta h}^2$	0.141	0.021	0.150	0.197

Table 4: GMM Forecasting Regressions of Returns and Rent Growth on Log Cap Rate for the 1985-2002 period

This table reports the two-stage GMM estimates for the regression of excess returns and rent growth between $t + 1$ and $t + k$ on the log cap rate at time t for the four commercial real estate property types. The moments are the OLS orthogonality conditions. In the system, horizons of $k = (2, 4, 8, 12)$ quarters are used. The estimation imposes the present value constraint (equation 17) and the short-long horizon relationship (equation 8) on the slope coefficients. The first stage weighting matrix is the identity matrix. The first stage estimator is then used to construct the optimal weighting matrix for the second stage, based on the Newey and West (1987) estimator with $q = 4$ lags. In the table, $\hat{\beta}_k^{adj}$ and $\hat{\lambda}_k^{adj}$ denote the bias-adjusted slope coefficients for the excess returns and rent growth regressions, respectively. The t -ratios t_{DR} are obtained using the double-resampling procedure described in Section 3.1. Statistical significance at the 5% and 1% level, evaluated using the empirical distribution from the double-resampling procedure, is denoted by superscripts a and b , respectively. The long-horizon coefficients β_k ($k \geq 4$) are obtained as $\beta_1(1 - \phi^k)/(1 - \phi)$, using the implied ϕ from the present value constraint. Their standard errors are then calculated using the delta method. The table also shows the R^2 for the OLS regressions of log cap rates on future returns (R_r^2) and on future rent growth ($R_{\Delta h}^2$), estimated separately. The sample is biannual observations of 21 areas from 1985:Q4 to 2002:Q4.

Apartments													Industrial			
k	$\hat{\beta}_{adj}$	t_{DR}	R_r^2	$\hat{\lambda}_{adj}$	t_{DR}	$R_{\Delta h}^2$	$\hat{\beta}_{adj}$	t_{DR}	R_r^2	$\hat{\lambda}_{adj}$	t_{DR}	$R_{\Delta h}^2$				
2	0.159	1.725	0.029	0.005	0.078	0.002	0.208	1.875	0.051	0.020	0.241	0.000				
4	0.299	1.790	0.055	0.009	0.079	0.001	0.385 ^a	1.953	0.098	0.036	0.241	0.000				
8	0.532 ^a	1.918	0.129	0.017	0.080	0.002	0.661 ^a	2.101	0.161	0.063	0.242	0.012				
12	0.713 ^a	2.040	0.217	0.022	0.080	0.015	0.860 ^a	2.234	0.229	0.081	0.243	0.050				
Retail							Offices									
k	$\hat{\beta}_{adj}$	t_{DR}	R_r^2	$\hat{\lambda}_{adj}$	t_{DR}	$R_{\Delta h}^2$	$\hat{\beta}_{adj}$	t_{DR}	R_r^2	$\hat{\lambda}_{adj}$	t_{DR}	$R_{\Delta h}^2$				
2	0.182 ^a	2.313	0.056	0.029	0.441	0.004	0.053	0.707	0.004	-0.036	-0.576	0.013				
4	0.343 ^a	2.380	0.114	0.055	0.442	0.001	0.103	0.712	0.012	-0.071	-0.575	0.012				
8	0.612 ^b	2.499	0.224	0.098	0.443	0.009	0.195	0.722	0.041	-0.134	-0.574	0.005				
12	0.822 ^b	2.596	0.327	0.132	0.444	0.047	0.279	0.732	0.080	-0.192	-0.573	0.002				

Table 5: Structural Parameters for the 1985-2002 period

Panel A of this table shows the underlying structural parameters of the model described in equations (9)-(12) for the four commercial real estate property types. The identification is obtained from the GMM estimates of Table 4 using the moment conditions as described in Appendix C. Panel B shows the implied annualized standard deviation of expected returns ($\text{std}(E_t r_{t+1})$), expected rent growth ($\text{std}(E_t \Delta h_{t+1})$), returns ($\text{std}(r_{t+1})$), and rent growth ($\text{std}(\Delta h_{t+1})$). Panel C shows the variance of expected returns as a fraction of total return variance (denoted by R_{Er}^2) and the variance of expected rent growth as a fraction of total rent growth variance ($R_{E\Delta h}^2$). Volatilities and covariances are expressed in annual terms. The sample is biannual observations of 21 areas from 1985:Q4 to 2002:Q4.

Panel A				
	Apartments	Industrial	Retail	Offices
ϕ	0.883	0.848	0.885	0.949
$\sigma_{\xi^x} \times 10^2$	1.946	1.701	1.377	1.414
$\sigma_{\xi^y} \times 10^2$	0.838	0.727	0.469	0.400
$\sigma_{\xi^h} \times 10^2$	4.306	4.928	3.478	5.153
τ	0.737	0.697	0.826	0.951
$\vartheta \times 10^4$	1.294	1.006	-0.141	0.321

Panel B				
	Apartments	Industrial	Retail	Offices
$\sigma_{\xi^r} \times 10^2$	8.498	7.414	4.606	7.260
$v \equiv \sigma_{\xi^y}^2 / \sigma_{\xi^x}^2$	0.186	0.183	0.116	0.080
$\text{std}(r_{t+1})$	0.095	0.081	0.055	0.085
$\text{std}(E_t r_{t+1})$	0.041	0.032	0.030	0.045
$\text{std}(\Delta h_{t+1})$	0.056	0.056	0.044	0.068
$\text{std}(E_t \Delta h_{t+1})$	0.035	0.026	0.026	0.045

Panel C				
	Apartments	Industrial	Retail	Offices
R_{Er}^2	0.192	0.158	0.292	0.278
$R_{E\Delta h}^2$	0.403	0.221	0.366	0.429

Table 6: GMM Forecasting Regressions of Returns and Rent Growth on Log Cap Rate

This table reports the two-stage GMM estimates for the regression of excess returns and rent growth between $t + 1$ and $t + 12$ on the log cap rate at time t for the four commercial real estate property types. The cross-section is equally split alternatively by population density and by the Growth Management Tool index measuring land use regulation. The moments are the OLS orthogonality conditions. In the system, horizons of $k = (1, 4, 8, 12)$ quarters are used. The estimation imposes the present value constraint (equation 17) and the short-long horizon relationship (equation 8) on the slope coefficients. The first stage weighting matrix is the identity matrix. The first stage estimator is then used to construct the optimal weighting matrix for the second stage, based on the Newey and West (1987) estimator with $q = 4$ lags. In the table, $\hat{\beta}_{12}$ and $\hat{\lambda}_{12}$ denote the bias-adjusted slope coefficients for the excess returns and rent growth regressions, respectively. The t -ratios, in parenthesis, are obtained using the double-resampling procedure described in Section 3.1 and the delta-method. The table also shows the implied structural parameters (τ, ν), the variance of expected returns as a fraction of total return variance (R_{Er}^2), and the variance of expected rent growth as a fraction of total rent growth variance ($R_{E\Delta h}^2$). The sample is quarterly observations of 53 areas from 1994:Q2 to 2003:Q1.

	Low-density				Low-regulation			
	Apt	Ind	Ret	Off	Apt	Ind	Ret	Off
β_{12}	0.699 (1.785)	0.691 (1.511)	1.126 (3.280)	0.511 (1.073)	0.346 (0.817)	0.760 (1.566)	1.146 (2.317)	0.651 (1.313)
λ_{12}	0.072 (0.227)	0.023 (0.055)	0.330 (0.799)	-0.142 (-0.358)	-0.121 (-0.428)	0.019 (0.042)	0.476 (0.773)	-0.076 (-0.133)
τ	0.415	0.653	0.703	0.446	0.622	0.232	0.722	0.649
ν	0.183	0.215	0.122	0.401	0.368	0.159	0.085	0.269
R_{Er}^2	0.071	0.117	0.266	0.040	0.056	0.040	0.228	0.069
$R_{E\Delta h}^2$	0.063	0.118	0.178	0.024	0.097	0.015	0.190	0.063
	High-density				High-regulation			
	Apt	Ind	Ret	Off	Apt	Ind	Ret	Off
β_{12}	0.277 (0.549)	0.568 (1.233)	0.841 (2.769)	0.161 (0.375)	0.652 (1.548)	0.577 (0.864)	0.874 (2.968)	0.108 (0.318)
λ_{12}	-0.145 (-0.403)	-0.216 (-0.442)	0.052 (0.157)	-0.526 (-1.284)	0.058 (0.157)	-0.094 (-0.171)	-0.002 (-0.007)	-0.559 (-1.870)
τ	0.826	0.147	0.662	0.973	0.661	0.182	0.651	0.980
ν	0.235	0.449	0.203	0.112	0.194	0.283	0.228	0.124
R_{Er}^2	0.107	0.030	0.143	0.283	0.117	0.041	0.195	0.292
$R_{E\Delta h}^2$	0.258	0.029	0.136	0.399	0.221	0.024	0.143	0.324

Table 7: GMM Forecasting Regressions of Returns and Rent Growth on Log Cap Rate and Principal Components of Economic Variables

This table reports the two-stage GMM estimates for the regression of excess returns (r column) and rent growth (Δh column) between $t+1$ and $t+k$ for the four commercial real estate property types. Regressors are the log cap rate at time t , the three principal components extracted from eight economic variables at time t , and a coastal dummy. In the system, horizons of $k = (4, 8, 12)$ quarters are used. The results refer to the 3-year ($k = 12$) horizon. The estimation imposes the present value constraint (equation 17) and the short-long horizon relationship (equation 8) on the slope coefficients. The first stage weighting matrix is the identity matrix. The first stage estimator is then used to construct the optimal weighting matrix for the second stage, based on the Newey and West (1987) estimator with $q = 4$ lags. In the table, cap denotes the bias-adjusted coefficient on the log cap rate. The t -statistics (in parenthesis below the estimates) are obtained using the double-resampling procedure described in Section 3.1. Statistical significance at the 5% and 1% level, evaluated using the empirical distribution from the double-resampling procedure, is denoted by superscripts a and b , respectively. The table shows two specifications for each real estate property type: (1) includes the cap rate, the three principal components and the coastal dummy, (2) includes just the principal components and the coastal dummy. The table also shows the R^2 for the corresponding OLS regressions for returns (R_r^2) and rent growth ($R_{\Delta h}^2$) at the $k = 12$ quarters horizon, estimated separately. The sample is annual observations of 53 areas from 1994 to 2001.

	Apartments				Industrial			
	r		Δh		r		Δh	
cap	0.791 ^b (3.682)	-	0.315 (1.913)	-	0.352 ^b (2.419)	-	-0.118 (-0.811)	-
pc_1	-0.013 ^a (-1.929)	-0.018 ^b (-2.832)	-0.011 (-1.721)	-0.012 ^b (-2.454)	-0.022 ^b (-4.797)	-0.009 (-1.813)	-0.029 ^b (-7.495)	-0.007 (-1.601)
pc_2	-0.027 ^b (-2.590)	-0.015 (-1.720)	-0.020 ^a (-1.979)	-0.016 ^b (-2.434)	-0.004 (-0.834)	-0.011 (-1.596)	-0.002 (-0.511)	-0.008 (-1.422)
pc_3	-0.010 (-1.177)	-0.001 (-0.106)	-0.014 ^a (-2.024)	-0.006 (-0.847)	-0.006 (-0.918)	-0.003 (-0.412)	-0.004 (-0.609)	-0.004 (-0.623)
coast	0.041 ^b (4.316)	0.028 ^b (2.897)	0.022 ^b (2.714)	0.013 (1.722)	0.020 ^b (3.295)	0.015 ^a (2.182)	0.016 ^b (3.208)	0.013 ^a (2.236)
R_{adj}^2	0.302	0.138	0.138	0.090	0.219	0.057	0.077	0.042
	Retail				Offices			
	r		Δh		r		Δh	
cap	0.914 ^b (5.236)	-	0.118 (0.625)	-	0.246 (1.309)	-	-0.370 (-1.830)	-
pc_1	-0.017 ^b (-4.581)	0.012 ^b (2.411)	-0.025 ^b (-7.217)	0.010 ^b (2.457)	-0.026 ^b (-3.786)	-0.005 (-0.602)	-0.034 ^b (-5.701)	-0.006 (-0.810)
pc_2	-0.011 ^b (-2.337)	-0.014 ^a (-2.055)	-0.013 ^b (-3.014)	-0.013 ^a (-2.238)	-0.005 (-0.625)	-0.027 ^b (-2.336)	-0.003 (-0.422)	-0.022 ^a (-2.246)
pc_3	-0.001 (-0.188)	0.002 (0.320)	-0.003 (-0.678)	0.002 (0.343)	-0.006 (-0.513)	-0.016 (-1.186)	-0.012 (-1.122)	-0.011 (-0.991)
coast	-0.003 (-0.550)	0.002 (0.357)	-0.004 (-0.940)	0.004 (0.986)	0.033 ^b (3.585)	0.043 ^b (3.259)	0.026 ^b (3.309)	0.033 ^b (2.513)
R_{adj}^2	0.368	0.063	0.136	0.073	0.169	0.123	0.101	0.096

Table 8: Portfolio Optimization

This table shows the optimal portfolio weights on stock and commercial real estate for the one-period quadratic utility maximization. For each asset, three specifications of weights are reported. The first specification corresponds to the unconditional problem, the second specification uses the dividend-price ratio as conditioning variable, the third specification conditions on both the dividend-price ratio and the cap rate. The corresponding average excess return of the optimal portfolio ($E(R_p)$), its standard deviation (σ_p), and its Sharpe ratio (SR_p) are also displayed. The annualized equalization fee is defined as fee that the investor would be willing to pay to have access to the conditional information. Bootstrapped t -statistics are shown in parenthesis below the estimates. The sample is biannual observations from 1986:Q2 to 2002:Q4.

		Unconditional case	Conditional on dp	Conditional on dp and cap
Stock	Constant	0.582 (2.889)	0.530 (2.912)	0.664 (2.711)
	dp		0.528 (2.060)	0.732 (2.388)
	cap			0.881 (2.182)
Cre	Constant	0.167 (0.223)	0.291 (0.388)	0.180 (0.233)
	dp		-1.627 (-2.650)	-1.141 (-2.163)
	cap			0.297 (2.198)
$E(R_p)$		0.037	0.084	0.132
σ_p		0.083	0.117	0.135
SR_p		0.446	0.716	0.976
Equalization fee			0.030	0.066

Figure 1: Cap rates and dividend-price ratio

This figure plots the cap rate for the commercial real estate (evaluated as average of the population-weighted averages of each property type) and the dividend-price ratio for the CRSP value-weighted portfolio, for the 1994:Q2 - 2003:Q1 quarterly series (top panel) and for the 1985:Q4 - 2002:Q4 semi-annual series (bottom panel). The dividend-price ratio series is break-adjusted in 1992.

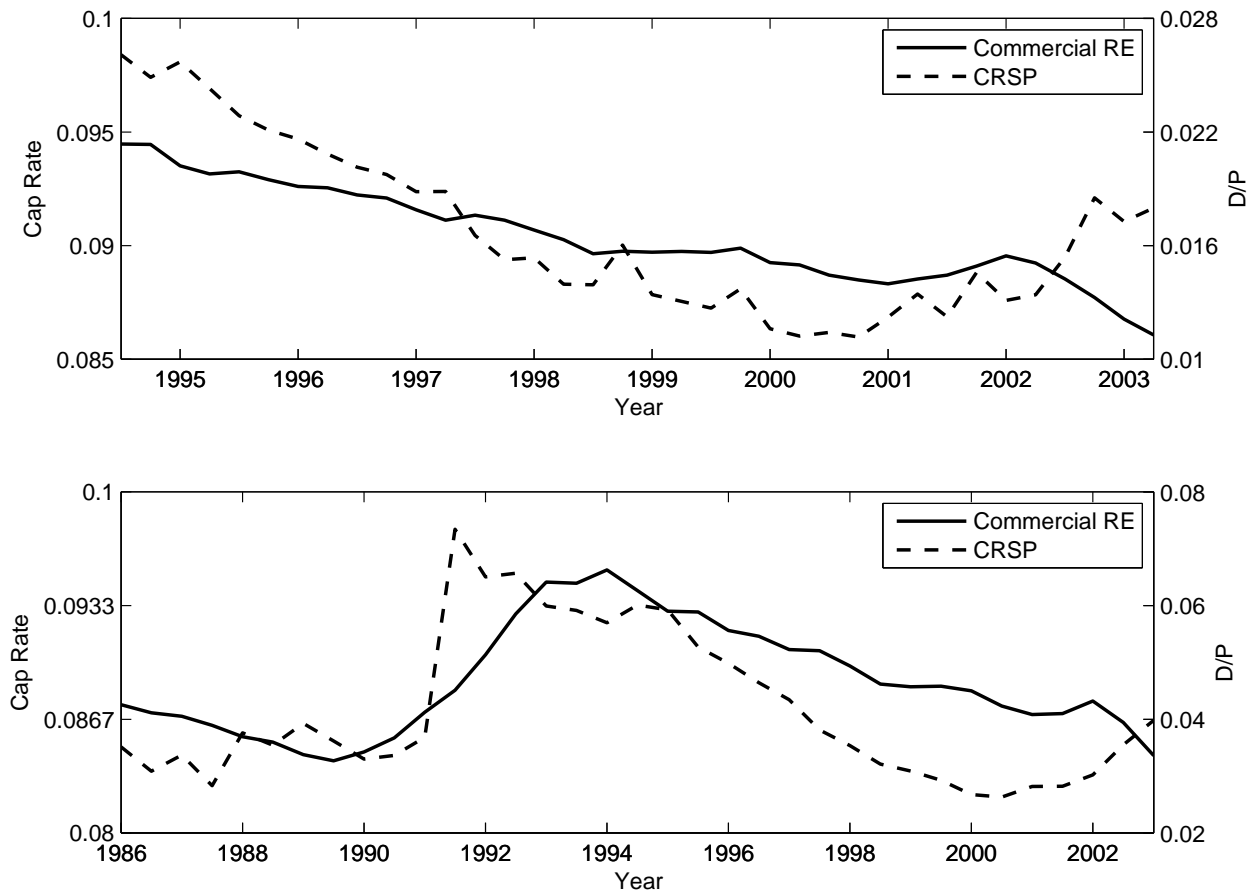


Figure 2: Cross-sectional dispersion in cap rates

This figure reports the 5th and 95th percentile (dotted line), and the mean (solid line) of the cross-sectional distribution of cap rates for the four property types. The sample is quarterly observations of 53 metropolitan areas from 1994:Q2 to 2003:Q1.

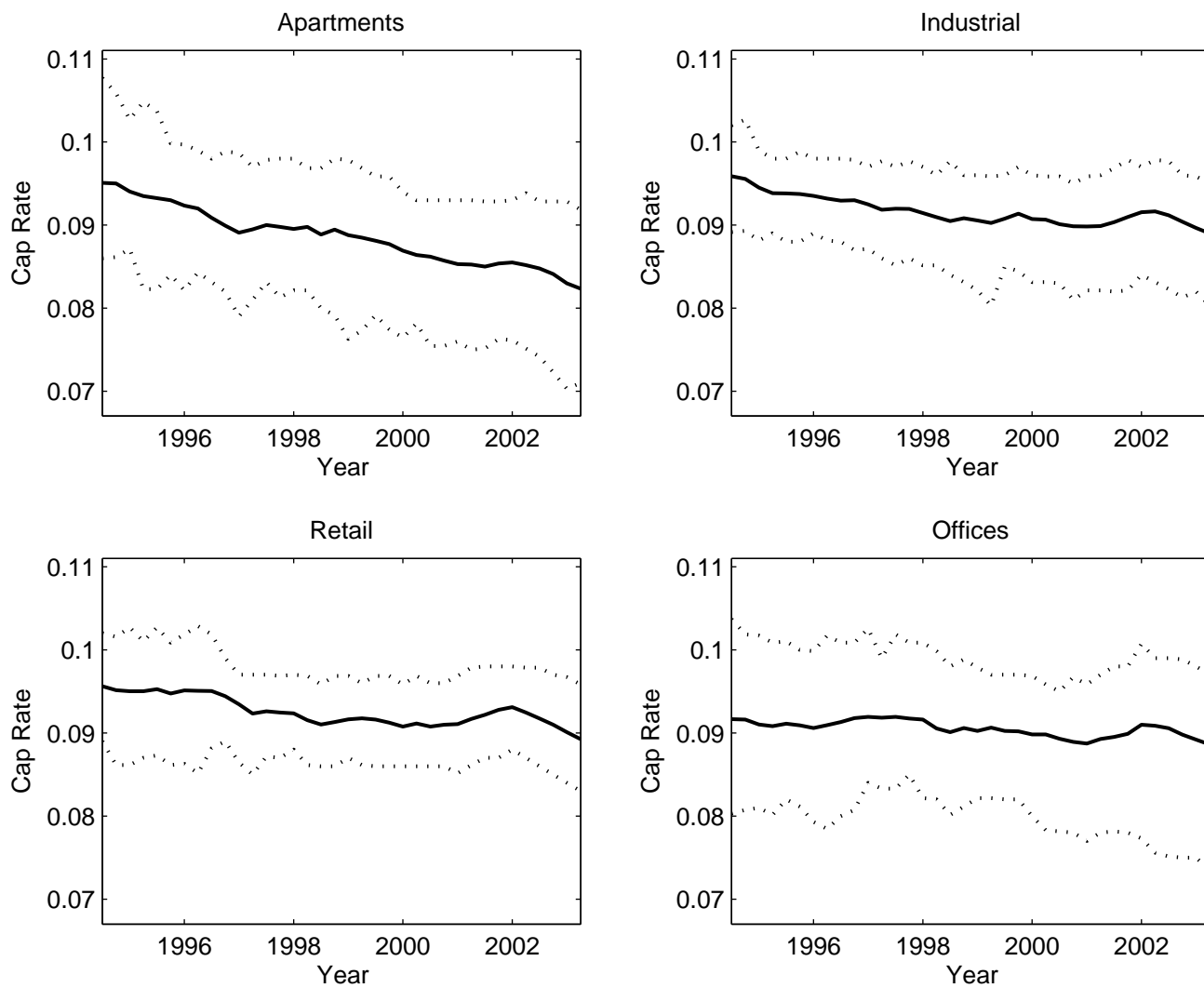


Figure 3: Beta and Lambda as a function of τ and v

This figure plots the slope predictive coefficients of the return regression β and rent growth regression λ , as function of the structural parameters τ (top two plots) and v (bottom two plots) using equations (15) and (16). In the expressions, we set $\phi = 0.95$ and $\rho = 0.98$.

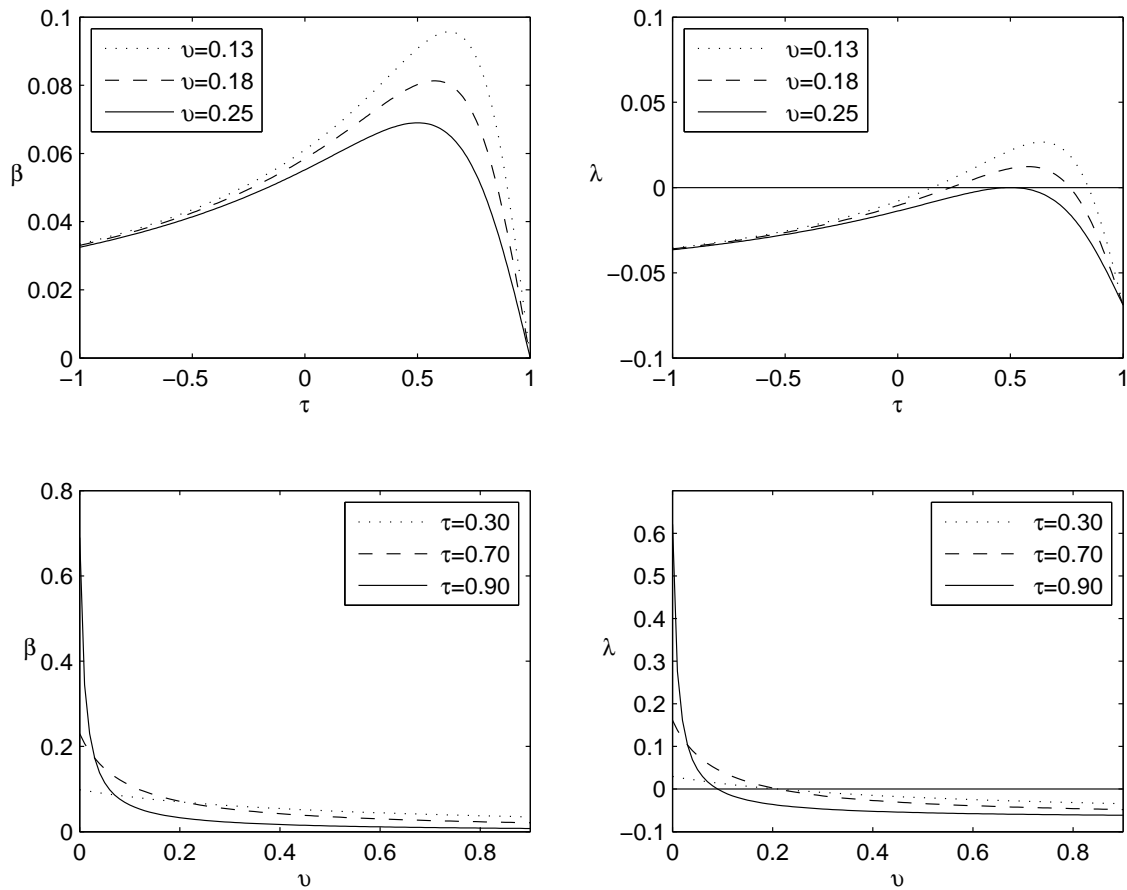


Figure 4: Portfolio weights on aggregate stock market and commercial real estate

This figure plots the time series of conditional portfolio weights on the stock (top panel) and on the aggregate commercial real estate (bottom panel). The dotted line displays the corresponding unconditional weights. The sample is biannual observations from 1986:Q2 to 2002:Q4.

